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What Drives the Joint Demand for Ride-hailing and Carsharing Services? Understanding Consumers' Behaviors, Attitudes, & Concerns

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ABSTRACT

Driven by the emerging collaborative consumption trends, new shared ownership-based business models provide more flexible and accessible on-demand mobility options. This study simultaneously analyzes factors correlated with the consumers' use of two interrelated disruptive on-demand mobility services, including ride-hailing (RH) and carsharing (CS). A comprehensive behavioral framework is presented to explicitly address important methodological concerns regarding the complex stochastic dependence between the use of CS and RH programs and the underlying behavioral heterogeneity in latent factors influencing the use of the two shared mobility options. Using unique data from the California Vehicle Survey, a rigorous elliptical and Archimedean copula based finite mixture bivariate ordered probit (BOP) modeling methodology is used to understand behavioral, attitudes, and concern-related correlates of households' participation levels in CS and RH programs. Characterized by a clayton-copula based finite mixture BOP model, participation levels in CS and RH programs exhibited complex (both synergistic and competing) non-linear stochastic dependence patterns. With a stronger left tail dependence, majority of the households having lower levels of participation in RH also had lower participation levels in CS programs. Contrarily, of the households with higher levels of participation in RH programs, the majority had lower levels of participation in CS programs (revealing weaker right tail dependence). Taste heterogeneity was observed in the unobserved determinants of CS use. Results show that current users of CS and/or RH programs tend to be those with greater awareness, owners of plug-in electric vehicles, those making greater transit trips, workers with greater commute distances, and those lacking free parking at their residences. Compared to ride-hailing, the negative effect of more frequent drivers in a household on CS use was less pronounced. Analysis of marginal and joint marginal effects provided deeper insights into the (interactive) effects of other behavioral and socio-demographic correlates. Treatment effects were simulated and discussed to further demonstrate the policy implications of our results. The new empirical insights provide a more granular understanding of the use patterns of on-demand shared mobility services and can inform more context-sensitive travel forecasts for planning and programming purposes.

Keywords: Carsharing, Ride-hailing, Use Patterns & Travel Forecasting, Heterogeneity, Elliptical/Archimedean Copula, Finite Mixtures, Bivariate Ordered Probit.

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1. INTRODUCTION

In the last decade, a marked shift has been witnessed in consumers' attitudes towards service consumption due to the rapid advancements in Information and Communication Technologies (ICTs) (Botsman and Rogers 2010). With a shift to peer-to-peer based activity (Hamari et al. 2016), an increase in consumers' preferences for accessing goods and services based on a shared ownership model is observed – avoiding the financial and environmental externalities often associated with personal ownership. The shared ownership model has also led to new ways for understanding our communities and addressing growing concerns about climate change, equity, social embeddedness, and distributed/communal (as opposed to centralized) consumption. With an estimated worldwide market of around $335 Billion by 2025, the concept of "collaborative consumption" or "shared economy" has led to new business models designed to respond to the needs of consumers across different sectors.

The impacts of shared economy are relatively more prominent in the transportation sector (De Lorimier and El-Geneidy 2013, Kopp et al. 2015, Wang et al. 2015, Shaheen and Chan 2016, Shaheen et al. 2016, Balac et al. 2017, Becker et al. 2018, Vinayak et al. 2018, Acheampong and Siiba 2020, Barbour et al. 2020, Khattak et al. 2020, Winter et al. 2021, Wali and Khattak 2022). The collaborative consumption-based mobility-on-demand services have led to more flexible, accessible, and convenient mobility options (Shaheen et al. 2015, Menon et al. 2019, Barbour et al. 2020). Among others, ride-sourcing or ride-hailing (on-demand ride services) and the latest forms of carsharing have emerged as two key mobility-on-demand services. On-demand ride services (or transportation network companies) connect consumers (riders) with the owners of personal vehicles willing to offer rides through smartphone-based applications (Shaheen and Chan 2016). Compared to traditional taxi, ridesharing offers a lower cost and convenient door-to-door mobility alternative with the potential to overcome first- and last-mile connectivity barriers. In addition, ridesharing services (such as Uber, Lyft) fill in gaps in the public transit network, provide connectivity to public transit, and complement public transit (and taxi) during specific times and geographical regions. With a global net revenue of $32 Billion (Iqbal 2023), around 131 million people used Uber app and around 7.6 billion trips were made by drivers in 2022, exceeding Uber's previous peak of 6.9 billion trips in 2019. At the same time, ridesharing and ride-hailing innovations face an uncertain regulatory and policy environment[2]. The manifestation and delivery of car sharing services through ICT and smartphones has revamped the utility and accessibility of traditional vehicle sharing programs tracing back to 1948 (Shaheen and Chan 2016). Car sharing services, such as ZipCar, car2go, and Getaround, allow users to enjoy the benefits offered by a private vehicle without incurring private ownership. In 2018, worldwide carsharing membership reached around 59 million – with a projected membership of 227 million users by the end of 2023 (Berg Insight 2023).

Given the immense growth in the popularity of ride-hailing and carsharing technologies in recent years, the present study focuses on analyzing the factors associated with the consumers' use of these two disruptive on-demand mobility services – with an emphasis on two key behavioral and methodological issues: investigating the stochastic dependence between the use of the two mobility services and the

[2] Shared mobility services were majorly disrupted by the COVID-19 pandemic. The advent of social distancing policies resulted in a sharp decrease in the use of public transport and shared mobility services (De Vos 2020, Shamshiripour et al. 2020); with further consequences also potentially hampering the promotion of shared automated vehicles (Shamshiripour et al. 2020, Wali and Khattak 2022). As the COVID-19 pandemic disrupted the world, it was highlighted that the widespread alterations in travel behavior, preferences, and risk perceptions exhibited during the COVID-19 pandemic will probably be sustained over a few years. Such modifications, meanwhile, are not expected to persist for very long (Bhat 2020, Menon et al. 2020). Recent evidence comparing the use of shared mobility services seemingly supports the expectation that individuals' travel behaviors and preferences will find an equilibrium over time and that revenues for shared mobility services will tend to match pre-COVID levels by 2021. As the pandemic started and evolved in 2020, TNCs (e.g., Uber and Lyft) observed a 90% reduction in the demand for ridesharing (Walters 2020, Curry 2022) and witnessed the lowest market size ($102 Billion in 2020 vs. $188 Billion in 2019). However, the market size increased to almost pre-pandemic levels in 2021 ($177 Billion) – reaching $201 Billion in 2022 (Curry 2022).

underlying behavioral heterogeneity in unobserved factors influencing the use of carsharing and ride-hailing programs. Beyond sociodemographic factors, the study contributes by shedding new light on how policy sensitive factors such as transit use, parking availability and associated costs, commute patterns, (electric) vehicle ownership, and awareness/concerns simultaneously relate to the use of carsharing and ride-hailing services. To achieve the objectives, unique and comprehensive data from the California Vehicle Survey are harnessed to specify advanced finite mixtures copula based joint bivariate ordinal discrete choice models for carsharing and ride-hailing use. To the best of our knowledge, the use of such an integrated framework is not reported in the context under discussion. Ride-hailing and carsharing are referred to as RH and CS in the paper.

The rest of the paper is structured as follows. Section 2 provides a synthesis of the relevant literature. We conclude section 2 by identifying the key gaps in our understanding of the factors associated with RH and CS use along with highlighting relevant methodological gaps. Section 3 presents the methodology used in the present study (including conceptual framework, data used, and methodological framework). Results are presented in section 4 followed by discussing and synthesizing the key findings in section 5. Policy implications of the results considering simulated treatment effects are also discussed in section 5. Limitations are identified in Section 6, and we conclude with the study in Section 7.

2. LITERATURE REVIEW

Both carsharing and ride-hailing mobility services have led to environmental and societal impacts[3]. Relative to the emerging ride-hailing services, the final commercial mainstreaming of the carsharing industry is reported to date back to 2007 (Shaheen et al. 2009). Subsequently, the impacts of CS on personal vehicle replacement, vehicle relinquishment, vehicles miles travelled (VMT) and greenhouse gas (GHG) emissions are relatively more examined (Ter Schure et al. 2012, Martin and Shaheen 2016, Shaheen and Chan 2016, Dill et al. 2019, Carrone et al. 2020). Regarding the frequency of CS use, previous studies have provided important insights mainly regarding the sociodemographic determinants. Younger individuals and males were correlated with greater use of CS (Habib et al. 2012, Chen et al. 2022). Higher education is also reported to be a predictor of greater CS membership or use (Costain et al. 2012, Dias et al. 2017, Aguilera-García et al. 2022). Mixed links between income and CS use have been reported with a negative association reported in some studies (Habib et al. 2012) – compared to no relationship between the two reported elsewhere (Wu et al. 2020, Li and Zhang 2023). Recent studies have emphasized the role of sociodemographic context driving CS usage (Aguilera-García et al. 2022). Likewise, the evidence regarding the links between vehicle ownership and CS use is mixed. Becker et al. (2017) and Kang et al. (2016) found a positive association between vehicle ownership and CS use (Kang et al. 2016, Becker et al. 2017). Contrarily, Wu et al. (2020) and Dias et al. (2017) found a lower propensity of CS use for individuals who owned vehicles (Dias et al. 2017, Wu et al. 2020). However, the negative impact of vehicle ownership on CS was less pronounced in denser areas (Dias et al. 2017). Notably, vehicle ownership was found to exhibit a moderating effect on the intention to use carsharing (Li and Zhang 2023). Evidence also suggests that CS

[3] The present study is positioned to gain a deeper understanding of the demographic, behavioral, and attitudinal factors jointly related to the use of carsharing and ride-hailing services with a methodological focus on capturing the joint stochastic dependence and underlying behavioral heterogeneity conveyed below. Thus, the forthcoming synthesis of the literature relates to the use patterns of the two disruptive shared mobility services. We acknowledge that shared mobility is an important but only one of the four key pillars (connectivity, automation, sharing, and electrification) of future smart cities. Not the focus of the present study, a growing spectrum of studies has examined the determinants of the adoption of different components of connected, automated, shared, and electric (CASE) vehicle systems, including partially and fully connected and automated vehicles (Shabanpour et al. 2018, Talebian and Mishra 2018, Menon et al. 2020, Wali et al. 2021, Asmussen et al. 2022), electric vehicles (Coffman et al. 2017, Xu et al. 2020, Asadi et al. 2021), and shared automated vehicles (Barbour et al. 2019, Spurlock et al. 2019, Wang et al. 2020, Wali and Khattak 2022, Etminani-Ghasrodashti et al. 2023). Integration of the multiple components of CASE vehicle systems will ultimately yield synergistic impacts on urban transportation systems (Stocker and Shaheen 2017, Narayanan et al. 2020).

may substitute public transit demand to some extent – with user dissatisfaction with transit services positively correlated with CS adoption (Acheampong and Siiba 2020). Besides sociodemographic factors, a handful of studies have examined behavioral factors and psychological attitudes in relation to CS use (Acheampong and Siiba 2020, Aguilera-García et al. 2022, Burghard and Scherrer 2022). These studies show that variety-seeking lifestyle, pro-environmental, and pro-technology attitudes predict carsharing use. However, evidence on the association of pro-environmental attitude with CS use is mixed – with pro-environmental attitudes positively associated with carsharing use in Ghana (Africa) (Acheampong and Siiba 2020), compared to a negative correlation between the two found in European cities (Aguilera-García et al. 2022).

Previous studies have also examined the characteristics of ride-hailing users. In particular, the relevance of RH in serving previously unmet demand for convenient door-to-door urban travel has been highlighted in the literature (Rayle et al. 2014). Research on RH adopters is still growing (Tirachini 2020), but some high-level conclusions can be made. High income, more educated, and/or younger individuals on-average had more RH use (Rayle et al. 2014, Dias et al. 2017, Lavieri and Bhat 2019) – with the choice and frequency of RH use driven by socioeconomic context (Soltani et al. 2021, Abouelela et al. 2022). Like car-sharing use, the potential impact of vehicle ownership in relation to RH was found to be mixed (Tirachini 2020). Vehicle availability was negatively correlated with RH frequency (Lavieri and Bhat 2019, Wang et al. 2021), whereas Tirachini and del Río (2019) noted a null association between the two (Tirachini and del Río 2019). From a behavioral and attitudinal standpoint, variety-seeking lifestyle propensity (a measure of an individual's willingness to experience new changes), environmental awareness, and attitudes/motives predict ride-hailing and (dynamic) ridesharing use[4] (Lavieri and Bhat 2019, Asimakopoulou et al. 2022, Si et al. 2022). Among the existing studies, only Dias et al. (2017) simultaneously analyzed the use of carsharing and ride-hailing services. However, the study did not consider two methodological issues of interest in the present study conveyed below, including the varying levels of stochastic dependence between carsharing and ride-hailing use and the underlying behavioral heterogeneity. The study also mainly focused on demographic and socioeconomic factors and was limited in its consideration of behavioral and attitudinal factors.

2.1. Research Gaps and Objectives

Overall, the valuable findings from the previous studies have important implications for transportation planning and travel demand modeling. We identify two gaps in the literature related to methodological issues and our existing understanding of the factors correlated with RH and CS use. Conceptually, previous studies have provided important insights largely focusing on socio-demographic factors. Little is known about how commute patterns, parking availability at home, and parking associated out of pocket costs correlate with the use of CS and RH services. While previous studies have shown mixed findings between conventional vehicle ownership and carsharing/ride-hailing, evidence is relatively scarce on how individuals with sustainable attitudinal predispositions (such as those owning electric vehicles) might use (not use) CS and RH services. Likewise, information on how transit use and awareness/concerns correlate with the consumers' use of CS and RH is relatively scarce. The present study examines the above policy-sensitive factors as it relates to the use of CS and RH services.

[4] We note that another stream of literature has meaningfully used aggregate spatiotemporal trip data (as opposed to individual-level survey data) provided by transportation network companies to understand the determinants of ride-hailing (Ghaffar et al. 2020, Marquet 2020, Belgiawan et al. 2022, Wali et al. 2022, Zhang and Zhao 2022) and dynamic ridesharing demand (Dean and Kockelman 2021, Du et al. 2022, Wali et al. 2022). Serving a different purpose, such aggregate data allows an examination of the spatiotemporal distribution of shared mobility services that can support resource planning and prioritization efforts. Individual-level variations in travel behaviors are masked nonetheless, making the use of such data not ideal for examination of the determinants of individual-level use of shared mobility services.

Methodologically, most previous studies are limited by focusing on either of the two (ride-hailing and carsharing) on-demand mobility services. Both RH and CS services are interrelated with the potential to play a pivotal role in overcoming critical gaps in the current transportation system (Shaheen and Chan 2016). RH and CS services encourage multimodality by providing first- and last-mile connectivity, providing an effective alternative to expensive shuttle/bus feeder services, complementing existing transit networks, and reducing the burden of land- and resource-intensive parking infrastructure (Shaheen and Chan 2016). As opposed to these synergistic relationships, competing relationships between RH and CS use may also exist. For instance, compared to RH, CS may be a more cost-effective option for individuals with longer-distance travel needs. Contrarily, due to their greater value of time, users with higher income may be more willing to use RH services and avoid the burden of driving themselves. Beyond observed factors, interactions between underlying unobserved factors can also simultaneously influence the use of CS and RH services. For example, not all attitudinal predisposition and lifestyle related factors can be observed in the data but may simultaneously influence the participation levels in CS and RH programs. Considering these multiple interactions, the present study presents a comprehensive and integrated behavioral framework for simultaneously modeling CS and RH use with two notable methodological extensions.

Compared to a standard joint modeling framework underpinned by a bivariate normality assumption, we employ a more rigorous elliptical/Archimedean copula-based discrete choice framework that provides a deeper understanding of the nature and extent of stochastic dependence (linear vs. non-linear) between CS and RH use. In doing so, the study captures non-linear stochastic dependence patterns between CS and RH use driven by competing and synergistic relationships between the two. A step further, the present study captures heterogeneity in unobserved or latent behavioral preferences for, and use of, emerging transportation options. To this end, we fuse finite mixture modeling methods with the copula-based joint discrete choice framework to obtain key insights about the underlying behavioral heterogeneity driven by unobserved and latent factors.

3. METHODOLOGY

3.1. Conceptual Framework

Figure 1 presents a general conceptual framework with a focus on understanding users' participation levels in CS and RH programs (dependent variables). The methodological framework recognizes that participation levels in CS and RH programs can be interdependent both due to the presence of common observed and unobserved factors. This possibility necessitates a joint estimation framework to simultaneously model the participation levels in CS and RH services.

While joint estimation leads to more efficient (precise) parameter estimates, the use of classical textbook based bivariate normal distribution is restrictive. It unrealistically posits that the (univariate) marginals describing the individuals' participation levels in CS and RH programs and the bivariate distribution (tracking stochastic dependence) itself belong to the same functional form family (Genest and Favre 2007, Nelsen 2007, Trivedi and Zimmer 2017). Additionally, the joint normality assumption may not always exist and can lead to behavioral unrealism in model interpretation. The bivariate normal distribution assumes a linear form of stochastic dependence between the two response outcomes (Yasmin et al. 2014, Wali et al. 2018). However, the stochastic dependence between unobservables associated with the two response outcomes may exhibit nonlinearity, i.e., weak stochastic dependence in the joint distribution tails and strong central dependence, or vice versa. This becomes highly relevant given the intrinsic differences between RH and CS programs discussed earlier (Shaheen and Chan 2016). The development of copula-based joint behavioral models enables modeling complex forms of stochastic dependence between the two response outcomes – in turn enhancing our understanding of the determinants of participation levels in CS and RH programs.

A step further, behavioral preferences for, and use of, emerging transportation options exhibit ubiquitous heterogeneity (de Ruijter et al. 2023, Zhong et al. 2023). In the copula based joint model, the marginals (holding the unobserved latent determinants of participation levels) for the two discrete ordered response outcomes are typically assumed to be homogeneous (Bhat and Eluru 2009, Yasmin et al. 2014, Wali et al. 2018). However, it is highly likely that the unobservables associated with CS and RH use exhibit heterogeneous clustering due to inherent differences among individuals. Thus, the study fuses finite mixture modeling techniques with copula-based joint behavioral framework – where the finite mixtures can capture potential heterogeneity in the univariate marginals (unobservables associated with the two response outcomes).

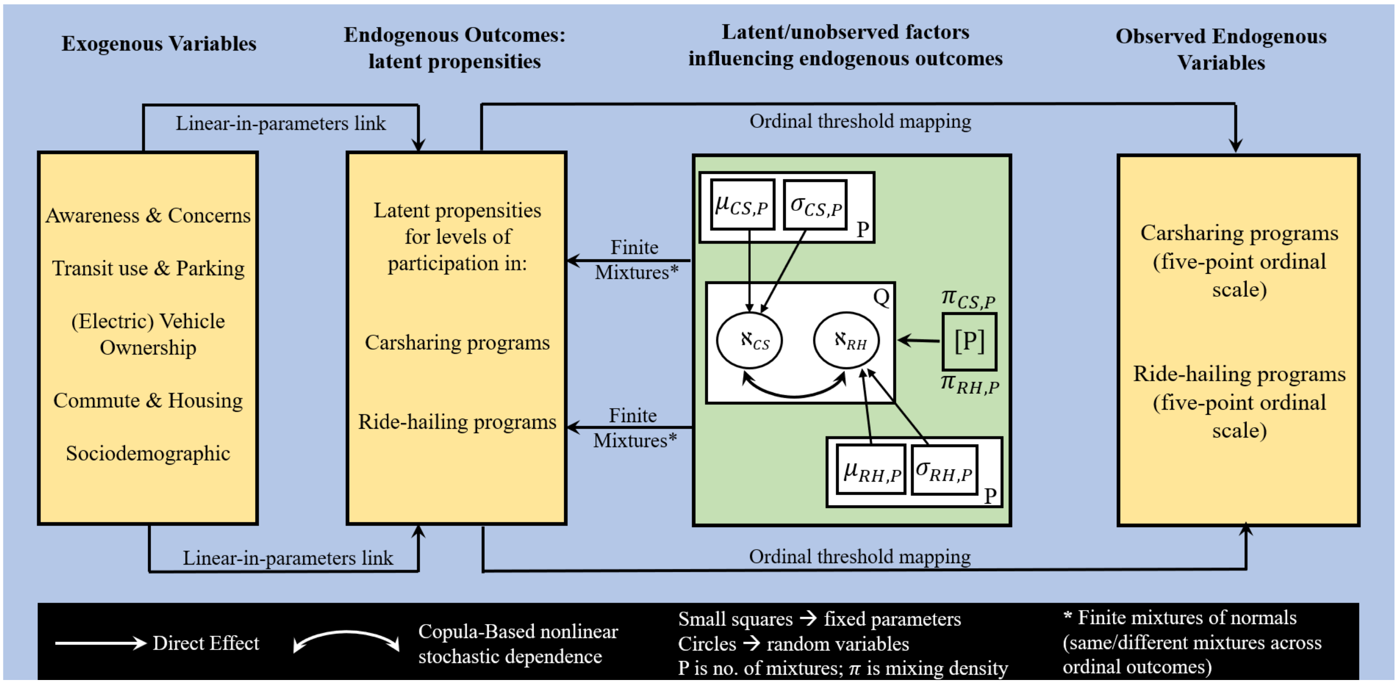

FIGURE 1. Copula Finite Mixtures Based Behavioral Model for Participation Levels in Carsharing (CS) and Ride-hailing (RH) Programs. Notes: Mixture models for latent factors shown using plate notation; Q is observation/household index; P is an index for the number of finite mixtures; Please zoom-in for better legibility.

3.2. Data Source

Data are derived from the unique and comprehensive 2017 California Vehicle Survey (CVS) to empirically test the conceptual model shown in Figure 1 (Fowler et al. 2017, TSDC 2017). The survey is part of the 2015-2017 California Vehicle Survey project providing information on travel behavior and activity-travel patterns, vehicle ownership patterns, opinions (attitudes) about (towards) emerging technologies, socio-economic, and demographic data for a representative and diverse sample of Californian households (Fowler et al. 2017, TSDC 2017). As preferences and vehicle technologies are quickly evolving over time, data from the CVS are used to forecast activity-travel demand and energy use in California. While not the focus of the present study, CVS integrates information on light-duty vehicle (LDV) ownership and use patterns with stated-preference based vehicle choice/preference data (both for residential and commercial LDV sectors).

Given the objectives (Figure 1), we integrate the main residential survey component with residential current vehicle and residential household survey modules (Fowler et al. 2017, TSDC 2017). The main residential survey is completed by the household head (18 years or older) responding to questions about their age, address, county, number of current household vehicles, parking availability and costs, leased or purchased vehicles over the last 10 years, plug-in electric vehicle ownership, and household size (Fowler et al. 2017, TSDC 2017). Additionally, the main residential survey includes two relevant questions on households' participation levels in CS and RH programs. Respondents (heads of the households) provided information on their participation levels in CS and RH programs by selecting one of the following categories:

- I am not interested in participating.
- I might participate someday.
- I have not participated in the past, but I plan to participate.
- I have participated in the past, but am not currently participation.
- I currently participate.

The participation levels in CS and RH programs serve as the two key response outcomes[5]. Respondents also provided information on the primary reason(s) they are not currently participating in carsharing or ride-hailing programs. To incorporate other policy-sensitive factors at the individual-level such as weekly transit use per member, work commute patterns for each commuter, frequent drivers, and detailed socio-demographic data, the main survey file was integrated and merged with current vehicle and individual member surveys. Since household serves as the unit of analysis, new variables on person and vehicle related factors aggregated to the household level were calculated. In summary, complete data on a total of 3600 households are used containing over 6000 and 8000 vehicles and individuals, respectively.

3.3.Analysis Framework – Heterogeneity-based Joint Estimation Framework

In this section, we provide a brief descriptive overview of the modeling framework. A comprehensive exposition (in light of the literature) of the copula-based finite mixture joint modeling framework adopted in this study is provided in Appendix A. An ordered discrete outcome modeling framework is employed since the two response outcomes, namely households' levels of participation in carsharing and ride-hailing programs, are each recorded as on a five-point scale with ordinal nature. Univariate ordered probit models can be used at a basic level to independently model participation levels in CS and RH programs (Greene 2003, Washington et al. 2020). However, given the dependencies between the two response outcomes highlighted in section 3.1, a joint discrete outcome estimation framework is needed that can model the joint probability distribution of participation levels in CS and RH programs (Eluru and Bhat 2007, Ma et al. 2018, Gkartzonikas and Dimitriou 2023). Thus, a bivariate ordered discrete modeling framework is implemented. Further, as detailed in Appendix A, a copula-based approach is harnessed to model different forms of stochastic dependence patterns between CS and RH use (Bhat and Eluru 2009, Yasmin et al. 2014, Wang et al. 2015, Wali et al. 2018, Shin et al. 2022, Wali et al. 2022). A diverse suite of elliptical and Archimedean copulas capturing symmetrical and asymmetrical (as well as linear and non-linear) stochastic dependence contours is used to model the joint distributions of carsharing and ride-hailing use patterns. While the copula approach can capture complex forms of stochastic dependence between the two response outcomes (Bhat and Eluru 2009), the typical application assumes homogeneity in the underlying marginals that construct the joint density of CS and RH use. In other words, the latent factors associated with carsharing and ride-hailing participation levels can exhibit heterogeneity derived from systematic variations in unobserved behavioral factors. Thus, we implement multi-component finite mixture models within the framework of a copula-based joint modeling approach. By capturing distributional bimodality and

[5] To elicit responses on the use of ridesharing services (Fowler et al. 2017), the California Vehicle Survey asked respondents: "What is your level of participation as a passenger in ride sharing and ride share programs, such as Uber, Lyft, Sidecar, etc.?" and "What is your level of participation in car-share programs where you can rent/access a car for short periods of time? Example car-share programs include Zipcar, Car2Go, CarShare, JustShareIt, RelayRides, etc.". While the terms "ride sharing" and "ride share" were used in the survey questions and the report, the question did not specify ridesharing options such as UberPool or LyftShare. Thus, to be conservative, we assume that the survey question solicited responses on the use of ride-hailing services.

skewness, the finite mixture modeling components can capture unobserved behavioral heterogeneity in the determinants of the use of CS and RH programs. Collectively, the fusion of finite mixture components with a copula-based joint discrete modeling framework enables more granular insights on the non-linear stochastic dependence and a fuller representation of the latent behavioral heterogeneity in unobserved factors predicting participation levels in the two shared mobility services. Details are provided in Appendix A.

4. RESULTS

4.1. Participation Levels in Carsharing and Ride-hailing Programs

Figure 2 shows an alluvial diagram to visualize the similarities and differences in consumers' participation levels in CS and RH programs. First, compared to carsharing programs, households on-average had greater participation levels in RH programs. Around 20% of the households currently participated in RH programs compared to only 4.1% of the households currently participating in carsharing programs (see Figure 2 and descriptive statistics in Table 1). These results align with the statistics reported elsewhere (Zhang and Zhang 2018, Tribby et al. 2020) – e.g., the national prevalence of taxi/ridesharing was found to be 1.1% (Tribby et al. 2020), suggesting that the use of shared mobility services is still not widespread. Second, a synergy (positive correlation) can be visually spotted between households' participation levels in CS and RH programs (Figure 2). However, contrasts are also observed especially in the lower and upper tails of the bivariate distribution. Most households who had lower levels of participation in RH also had lower participation levels in CS programs (green chords running between levels [1] and [2] for RH and CS programs in Figure 2). This shows a relatively stronger dependence in the lower tail of the bivariate distribution. Contrarily, most households who had higher levels of participation in RH had lower levels of participation in CS programs (red chords running between levels [4] and [5] for the two outcomes in Figure 2). In line with the conceptual framework (section 3.1), this shows at a visual level that the stochastic dependence in the upper tail of the bivariate distribution is relatively less synergistic. These findings support the hypothesized synergistic and competing relationships discussed earlier between the two shared mobility options. It also indicates the possibility of a strong non-linear stochastic dependence between the households' use of CS and RH services as opposed to a linear stochastic dependence. Finally, some households had relatively lower participation levels in RH compared to their participation levels in CS (blue chords in Figure 2).

4.2.Descriptive Statistics

Table 1 shows the descriptive statistics for the key explanatory variables. Around 2.3% and 10.6% of the households were (self-reportedly) not aware of ride-hailing and carshare programs, respectively. Whereas another 2.8% and 3.4% of the households found these programs too expensive/unaffordable. On average, household members made around 1.13 one-way transit trips per week but with significant variations across the sampled households (Table 1). In terms of parking, around 6.7% of the households paid for parking at their residences whereas another 54.1% had access to personal garages for parking. The average number of vehicles and plug-in electric vehicles in the sampled households was 1.94 and 0.21, respectively. Commuters on average travelled (one-way) 11.64 miles. Descriptive statistics for other sociodemographic factors are shown in Table 1. Overall, the data seems to be of reasonable quality based on the descriptive statistics and the fact that the data are extracted from a well-integrated statewide survey system on emerging transportation modes.

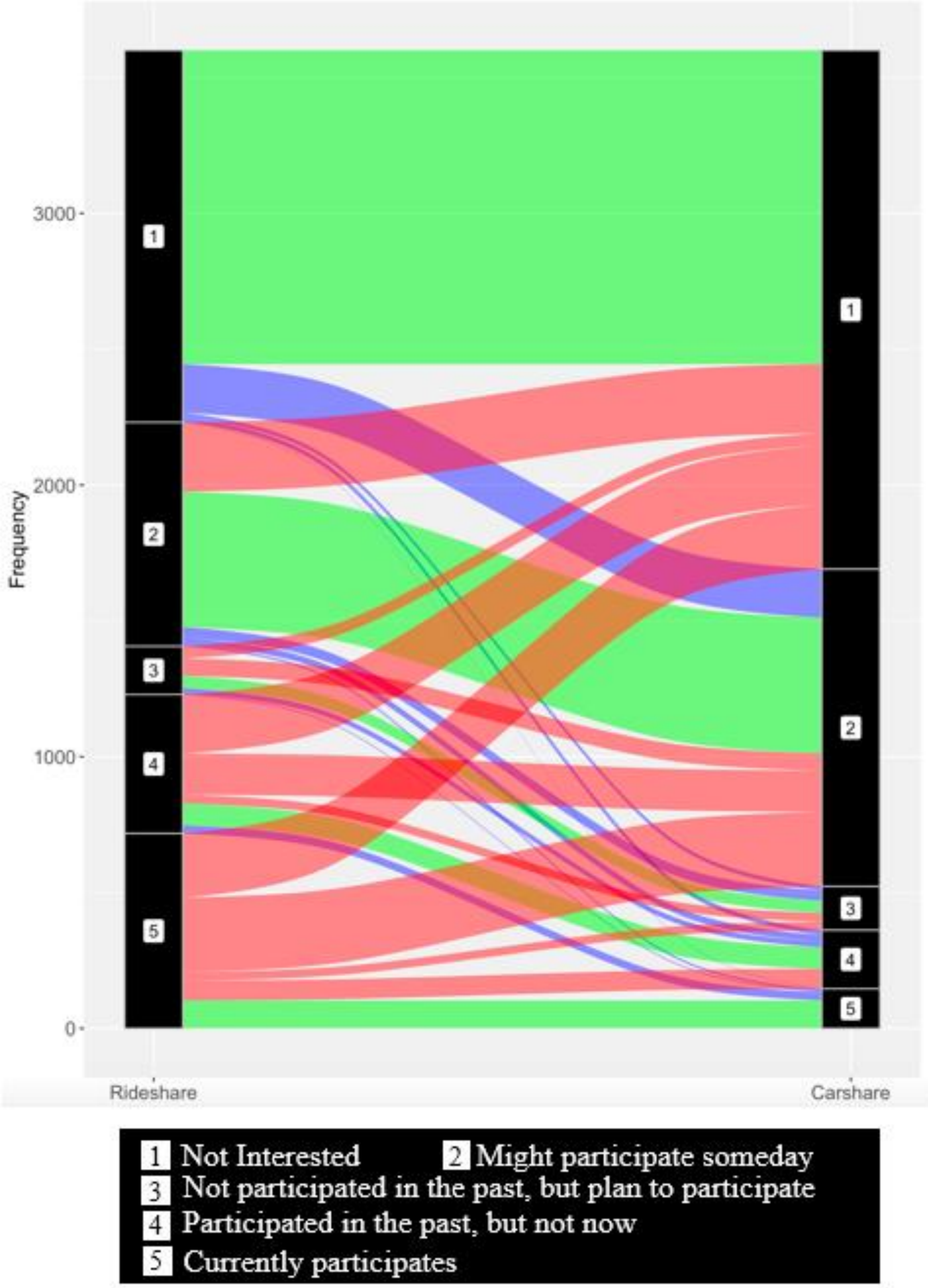

Figure 2. Alluvial Diagram of Consumers Participation Levels in Carsharing and Ride-hailing Programs. Notes: Frequencies for each category of response outcome are plotted vertically on the stacked bars; the chords show the proportion of respondents having a particular participation level in CS and RH programs (N = 3,600); empirical Kendall τ correlation coefficient = 0.40.

TABLE 1. Descriptive Statistics of Key Variables

Category	Variables	Mean	SD	Min	Max
Level of Participation in RH and CS Programs	RH: Not interested	0.380	0.486	0	1
	RH: Might participate someday	0.229	0.420	0	1
	RH: Has not participated in the past, but plan to participate	0.049	0.217	0	1
	RH: Participated in the past but not now	0.142	0.349	0	1
	RH: Currently Participates	0.199	0.400	0	1
	CS: Not interested	0.530	0.499	0	1
	CS: Might participate someday	0.324	0.468	0	1
	CS: Has not participated in the past, but plan to participate	0.045	0.207	0	1
	CS: Participated in the past but not now	0.060	0.238	0	1
	CS: Currently Participates	0.041	0.197	0	1
Awareness & Concerns	RH programs: Not aware	0.023	0.151	0	1
	RH programs: Too expensive/unaffordable	0.028	0.165	0	1
	RH programs: Not available in area	0.041	0.198	0	1
	RH: Public transit already meets my needs	0.030	0.171	0	1
	CS programs: Not aware	0.106	0.308	0	1
	CS programs: Too expensive/unaffordable	0.034	0.181	0	1
	CS programs: Not available in area	0.095	0.293	0	1
	CS: Public transit already meets my needs	0.024	0.154	0	1
Transit Use, Parking, Housing	Average weekly one-way transit trips per member*	1.133	3.866	0	100
	Pay to park at residence	0.067	0.250	0	1
	Amount paid to park (in USD)	5.005	34.365	0	500
	Parking type: personal garage	0.541	0.498	0	1
	Housing: Apartment	0.196	0.397	0	1
(Electric) Vehicle Ownership & Commute Distance	Number of plug-in electric vehicles (PEVs)*	0.210	0.734	0	8
	Number of household vehicles*	1.942	0.936	1	8
	Average one-way commute distance per commuter in household*[a]	11.647	18.966	0	200
	Missing commute distance dummy*[a]	0.320	0.466	0	1
	Number of frequent drivers in household*	1.490	0.822	0	7
Sociodemographic Factors	Number of household members*	2.458	1.261	1	13
	Number of members with postgraduate degrees*	0.512	0.703	0	3
	Number of members with some college education*	0.349	0.623	0	6
	Number of females*	1.044	0.607	0	5
	Number of fulltime workers*	0.912	0.844	0	8
	Number of retired individuals*	0.744	0.826	0	6
	Number of fulltime students*	0.093	0.349	0	5
	Income: Less than $50,000 (base)	0.238	0.426	0	1
	Income: $50,000 to $74,999	0.185	0.388	0	1
	Income: $75,000 to $99,999	0.175	0.380	0	1
	Income: $100,000 to $149,999	0.220	0.414	0	1
	Income: $150,000 or more	0.182	0.386	0	1

Notes: N is 3600; SD is standard deviation; RH is ride-hailing & CS is carsharing. All variables are dummy variables (except indicated otherwise). (*) indicates derived variables that are computed at the household-level using person- or vehicle-level data files. (a) The variable 'average one-way commute distance per commuter in household' has 'missing' values due to non-commuters (~32%) in the sampled households. To use the entire sample in model estimation, we replaced the 'missing' values with 0 and subsequently created a dummy variable which is 1 if the average commute distance was replaced with 0, and 0 otherwise.

We use both variables in the subsequent empirical models. In other words, the missing commute distance dummy captures non-commuters in a household.

4.3.Modeling Results

For model selection, Information Theoretic Approach is used, namely Akaike Information Criterion (AIC) and Schwarz/Bayesian Information Criterion (SIC/BIC) (Bozdogan 2000, Neath and Cavanaugh 2012). Lower AIC or BIC values indicate better fit after accounting for model complexity and predictive ability (Bhat and Sener 2009). Initially, two univariate ordered probit models were developed for modeling households' participation levels in CS and RH programs. Next, an elliptical Gaussian copula based bivariate ordered probit (BOP) model was developed. Precisely, the Gaussian copula-based BOP model accounted for the simultaneous correlation between the unobserved factors underlying the participation levels in CS and RH programs. Compared to the independent models, the AIC and BIC of Gaussian copula-based BOP model reduced by around 640 and 634 points (Table 2). Broadly, a difference of around 5 points between two AIC or BIC values provide strong statistical evidence in favor of the model with the lowest AIC/BIC (Bozdogan 1987, Burnham and Anderson 2004). This remarkable reduction in the AIC and BIC for Gaussian copula-based BOP model signifies the presence of significant interdependence between the unobservables underlying households' participation levels in CS and RH programs – even after controlling for a host of observed explanatory variables.

4.3.1. Non-Linear Stochastic Dependence

While the Gaussian copula-based BOP model exhibited significantly better goodness of fit, it assumed a linear form of stochastic dependence between the two response outcomes. To systematically examine different (non-linear) stochastic patterns, a series of Archimedean copula-based BOP models (Clayton, Frank, Gumbel, and Joe) were developed next. For brevity, we only show the final goodness-of-fit measures of different Archimedean copula-based BOP models (Table 2). Among the four Archimedean copulas, the Clayton copula-based BOP resulted in the lowest AIC and BIC (Table 2). Compared to the Gaussian copula-based BOP model, the BIC of clayton copula-based BOP model reduced by around 88 points. This finding suggests that not only are the unobservables underlying CS and RH use correlated, but that a significant non-linear stochastic dependence pattern exists between the two. Figure 3 shows the predicted probabilities of a household currently participating in CS programs (highest participation level) and not interested in CS programs (lowest participation level) conditional on the household's observed RH participation levels. Since the independent models do not consider the stochastic dependence between the two mobility options, the probability of a specific level of carsharing use (e.g., current participation) does not vary across the levels of ride-hailing use (horizontal line in Figure 3). The heterogeneous joint models consider the stochastic dependence and thus the probability profiles are not flat for the copula-based models. Compared to the best-fit Clayton copula model (green line in Figure 3), Gaussian, Frank, Joe, and Gumbel copula models underestimated the probability of the highest participation level in CS for households with lower levels of RH participation; and overestimated the likelihood of CS use for households with highest RH participation levels (left figure in Figure 3). Similar under- and over-estimation patterns can be observed for the probability of households not interested in CS programs (lowest level) conditional on their participation levels in RH programs (right figure in Figure 3).

TABLE 2. Goodness of Fit Measures for Copula-Based Bivariate Ordered Probit Models

Variable	Independent	Gaussian	Frank	Gumbel	Joe	Clayton
Sample size (N)	3600	3600	3600	3600	3600	3600
No. of parameters (K)	44	45	45	45	45	45
Log-likelihood at zero, LL(0)	-9330.77	-8917.348	-8917.348	-8917.348	-8917.348	-8917.348
Log-likelihood at convergence, LL(β)	-8905.96	-8584.83	-8588.088	-8635.462	-8698.89	-8540.488
Akaike Information Criterion (AIC)	17899.92	17259.66	17266.18	17360.92	17487.79	17170.98
Bayesian Information Criterion (BIC)	18172.23	17538.15	17544.67	17639.41	17766.28	17449.47

Notes: Independent means two univariate ordered probit models for participation levels in carsharing and ride-sourcing programs; Other columns show the results for copula-based bivariate ordered probit models.

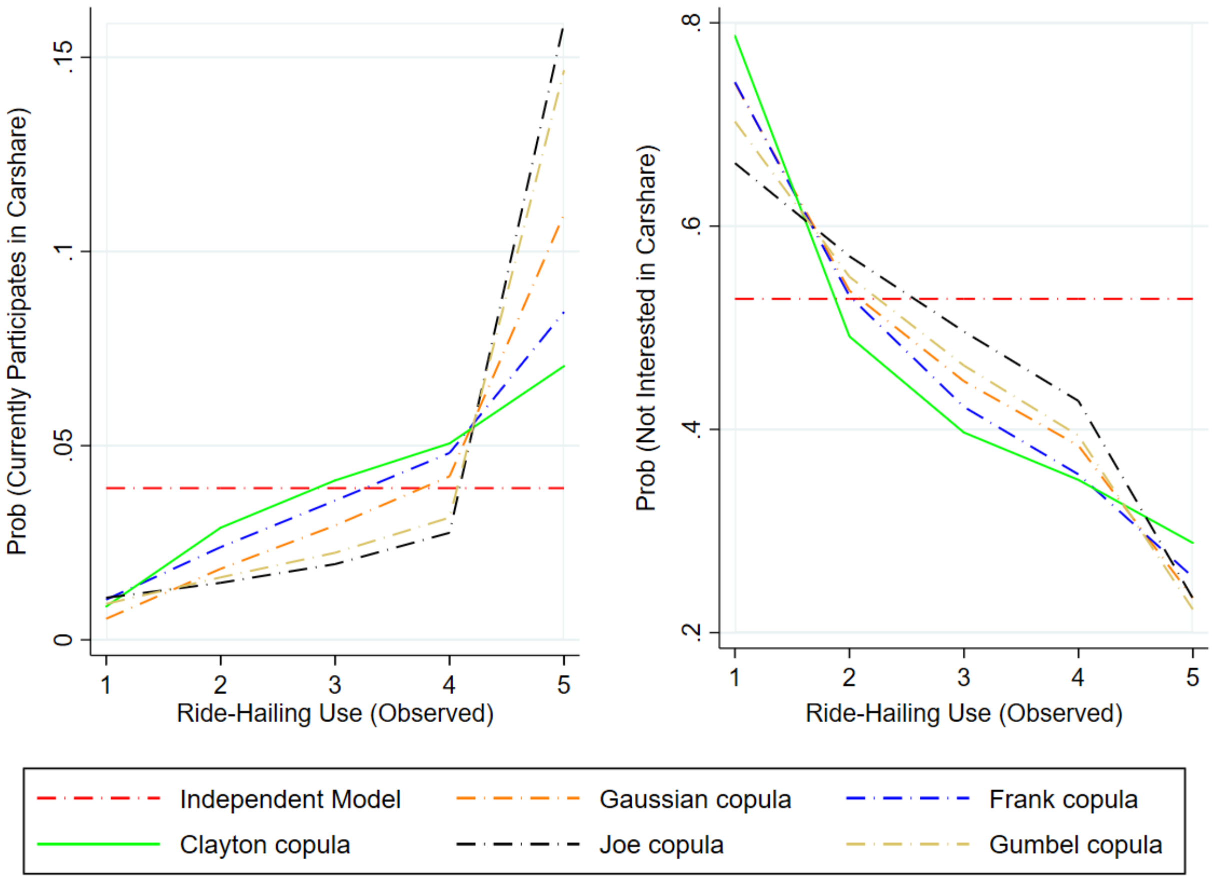

Figure 3. Simulated Probabilities of Households Currently Participating in Carsharing Programs (highest level) and Not Interested in Carsharing (lowest level) Conditional on Their Participation Levels in Ride-Hailing Programs. Notes: Ride-hailing use: 1 - not interested; 2 is might participate someday; 3 is not participated in the past, but plan to participate; 4 is participated in the past, but not now; 5 is currently participates.

4.3.2. Finite Mixture Heterogeneity in Latent Factors

Using the best-fit Clayton copula BOP specification, we examined potential heterogeneity in the latent factors underlying households' participation levels in CS and RH programs by estimating a series of finite mixture Clayton copula BOP models. For the two marginals associated with CS and RH use, we tested the following schemes: (1) a two-part finite normal mixture for RH and a standard normal *N(0,1)* for CS; (2) a *N(0,1)* for RH and a two-part finite mixture marginal for CS; (3) different finite mixture marginals for CS and RH; (4) same finite mixture marginals for CS and RH. Table 3 shows the goodness of fit results for the clayton-copula based finite mixture BOP models. A two-part finite mixture marginal for CS (and normal marginal for RH) resulted in the lowest AIC and BIC (Table 3). Precisely, compared to the standard homogenous Clayton-copula BOP model, the AIC and BIC for the best-fit Clayton finite mixture BOP model reduced by around 67 and 48 points respectively (Table 3) – suggesting significant mixture heterogeneity in the unobservables associated with participation in CS programs. Referring to Table 4, the estimated finite mixture for CS is a mixture of a bimodal distribution with two dominant components – mixture weight ($\pi_{\aleph_{Ql_K}}$) of 0.49, centered above zero ($\mu_{1,\aleph_{Q_{l_K}}} = 0.69$) but relatively less dispersed ($\sigma_{1,\aleph_{Q_{l_K}}} = 0.473$) compared to an equally dominant more dispersed component centered below zero ($\mu_{2,\aleph_{Q_{l_K}}} = -0.677$ and $\sigma_{2,\aleph_{Q_{l_K}}} = 0.913$) (see Appendix A for notation; Q is an index for household; l_K represents the ordinal participation levels in CS ($K = 1$) and RH ($K = 2$) programs). To visualize the patterns of mixture heterogeneity, Figure 4 shows the estimated two-part normal mixtures for CS and the estimated finite mixture of the two distinct components of the latent factors underlying households' participation in CS programs. We note that while the AIC and BIC for Clayton copula model with same marginal mixtures for both RH and CS are somewhat similar to the best-fit mixture model (see Table 3), the parameter estimates for mixing distributions were statistically insignificant (results not shown here). Likewise, while the AIC of the Clayton copula finite mixture model with different marginal mixtures for RH and CS was slightly better than the best-fit model (although the BIC was worse) (Table 3), the mixing distributions were nonetheless statistically insignificant. In summary, the Clayton copula-based joint model with a two-part normal mixture marginal for CS use was chosen as the best-fit model.

TABLE 3. Goodness of Fit Measures for Best-Fit Clayton Copula Based BOP Model with Finite Mixture Heterogeneity

	Best-Fit Clayton Copula Based Joint Bivariate Ordered Probit Model				
Variable	**RH & CS Marginals: Both *N(0,1)***	**RH Marginal: *Two-part Normal*; CS Marginal: *N(0,1)***	**RH Marginal: *N(0,1)*; CS Marginal: *Two-part Normal****	**RH & CS Marginals: Each with *different marginal mixture distribution***	**CS & RH Marginals: Both have *same marginal mixture distribution***
Sample size (N)	3600	3600	3600	3600	3600
No. of parameters (K)	45	48	48	51	48
Log-likelihood at zero, LL(0)	-8917.35	-8917.35	-8917.35	-8917.35	-8917.35
Log-likelihood at convergence, LL(β)	-8540.49	-8534.78	-8503.74	-8497.89	-8504.42
Akaike Information Criterion (AIC)	17170.98	17165.55	17103.47	17097.78	17104.83
Bayesian Information Criterion (BIC)	17449.47	17462.61	17400.53	17413.40	17401.89

Notes: RH is ride-hailing; CS is carsharing. (*) The Clayton copula-based joint model with a two-part normal mixture marginal for CS use served as the best-fit model (as discussed in text).

TABLE 4. Thresholds, Copula Dependence, and Mixture Heterogeneity Parameters for Gaussian, Clayton, and Finite Mixture Clayton-Based BOP Models

Category	Variable	Gaussian Copula Based Bivariate Ordered Probit Model		Clayton Copula Based Bivariate Ordered Probit Model		Best-Fit Clayton Copula with Heterogeneous Mixtures Based Bivariate Ordered Probit Model	
		RH Use	CS Use	RH Use	CS Use	RH Use	CS Use
		β [t-stat]	β [t-stat]	β [t-stat]	β [t-stat]	β [t-stat]	β [t-stat]
Unobservables - Dependence & Mixture Heterogeneity	**Effects of Unobservables**						
	Constant	-0.100 [-1.29]	0.349 [3.74]	-0.083 [-1.17]	0.326 [3.47]	-0.092 [-1.39]	0.477 [5.35]
	Threshold 1	0.532 [6.28]	1.387 [17.69]	0.553 [7.19]	1.369 [17.53]	0.539 [7.34]	1.267 [18.65]
	Threshold 2	0.667 [8.1]	1.632 [18.47]	0.690 [9.08]	1.619 [17.7]	0.675 [9.37]	1.427 [18.26]
	Threshold 3	1.111 [12.61]	2.175 [28.93]	1.147 [13.79]	2.164 [27.97]	1.129 [14.24]	1.769 [14.76]
	Copula Dependence Parameters						
	Lambda (λ)	0.576 [17.13]		0.234 [2.38]		0.275 [2.75]	
	Copula dependence parameter [α]	0.521 [21.77]		1.264 [10.133]		1.316 [9.98]	
	Kendall τ	0.353		0.396		0.401	
	Clayton lower tail dependence ($2^{-\alpha}$)	---		0.591		0.602	
	Mixture Heterogeneity for CS Use						
	Mixture of Normals: Component 1						
	Mixing Parameter ($\pi_{\aleph_{Ql_K}}$)	---		---		0.495 [7.96]	
	Mean Parameter ($\mu_{1,\aleph_{Ql_K}}$)	---		---		0.691 [10.73]	
	Standard deviation ($\sigma_{1,\aleph_{Ql_K}}$)	---		---		0.473 [1.761]	
	Mixture of Normals: Component 2						
	Mixing Parameter ($1 - \pi_{\aleph_{Ql_K}}$)	---		---		0.504 [8.12]	
	Mean Parameter ($\mu_{2,\aleph_{Ql_K}}$)	---		---		-0.677 [-5.42]	
	Standard deviation ($\sigma_{2,\aleph_{Ql_K}}$)	---		---		0.913 [3.05]	

Notes: --- is not applicable; For notations – see section Appendix A.

Besides the mixture heterogeneity in CS use, the best-fit Clayton copula joint model implies a non-linear stochastic dependence between the unobservables underlying participation in CS and RH programs. The non-linear stochastic dependence pattern is illustrated in Figure 5 which contrasts the estimated interdependence between the unobservables for the two response outcomes obtained from the traditional Gaussian copula and the best-fit Clayton copula BOP model with two-part mixture for CS outcome. In addition, Table 4 shows the copula-dependence parameters (and associated Kendall's τ values) for the Gaussian and the best-fit clayton copula-based finite mixture BOP models. Importantly, the α (copula dependence) parameter for Clayton copula is 1.316 with a t-statistic of 9.98 – translating to a sizeable Kendall's τ of 0.401[6] (Table 4). Further, the significant lower tail dependence parameter reflects a relatively

[6] We note that other studies have found dependence parameters of a similar magnitude between different configurations of the components of (automated) shared mobility services (Lavieri and Bhat 2019, Wali

stronger stochastic dependence in the left tail of the distribution (compared to the center of the distribution) (see Table 4 and Figure 5). Contrarily, Gaussian copula assumes zero dependence in the tails of the distribution and such deeper insights can thus not be obtained. Table 5 shows the estimation results for the best-fit Clayton copula-based BOP model with finite mixtures for unobservables associated with CS use. The results for standard Gaussian- and Clayton-copula based BOP models with homogeneous marginals are also presented for comparative purposes.

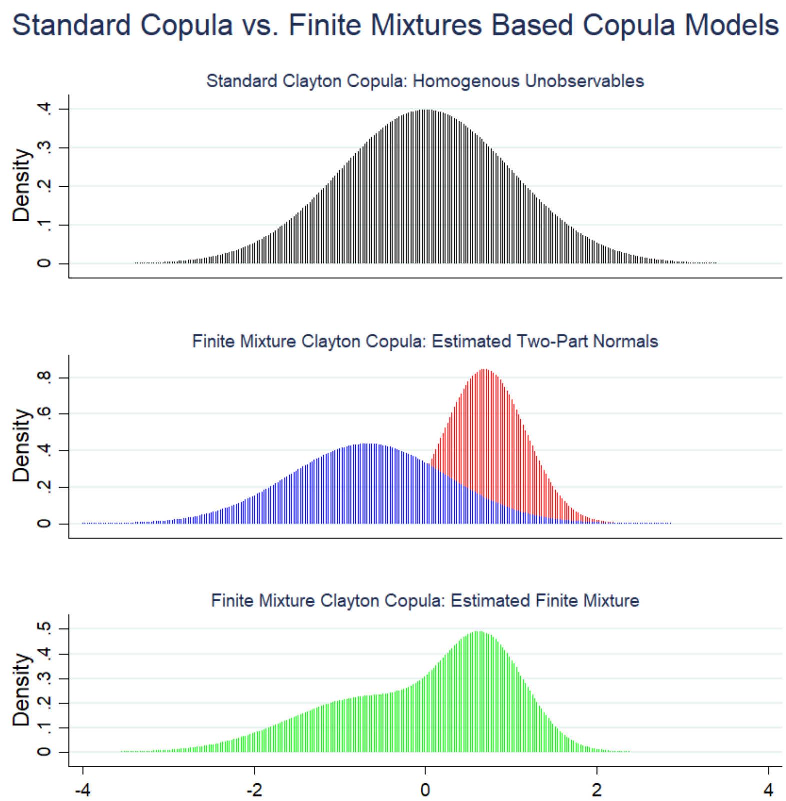

Figure 4. Best-Fit Heterogeneous Finite Mixture Clayton Copula Model - Estimated Finite Mixture Density of the Latent Factors Underlying Households' Participation in Carsharing Programs.
Notes: See Table 4 for mixing, location, and scale parameters.

and Khattak 2022). Studies show that accounting for even weaker error correlations (e.g., in the range of 0.1 to 0.3) can provide deeper insights and meaningful gains in model goodness of fit (Dias et al. 2019, Loa et al. 2021, Rahman et al. 2021).

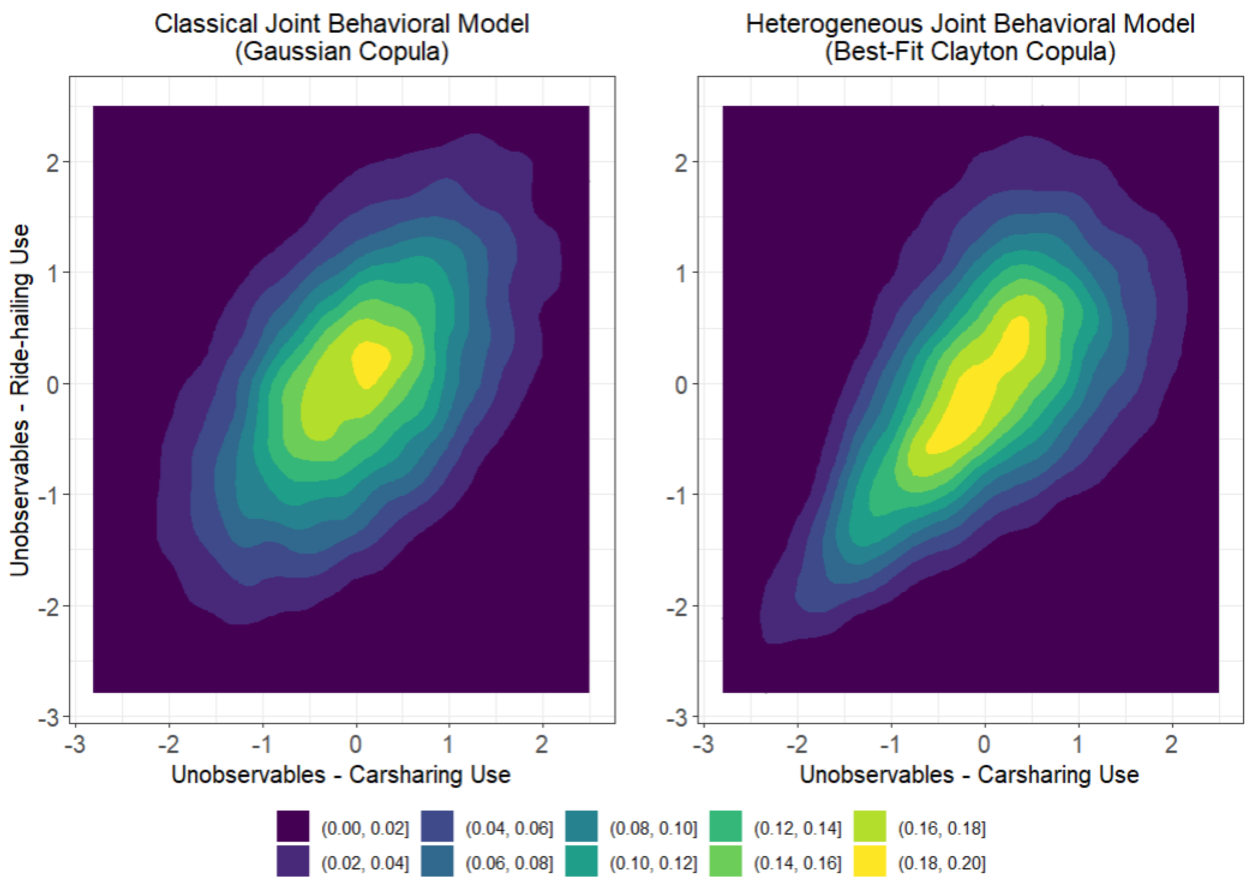

Figure 5. Estimated Stochastic Dependence Patterns Between Unobservables for Participation Levels in Carsharing and Ride-hailing Outcomes. Notes: The plasma shows the density of points under the traditional and best-fit heterogeneous joint behavioral model.

5. DISCUSSION & SYNTHESIS

The finding that the unobservables associated with CS and RH use exhibited a nonlinear stochastic dependence is consistent with expectations and has important behavioral and practical implications (Figure 5). Behaviorally, the positive Kendall's τ of 0.401 suggests that latent factors that positively influence the participation levels in one of the two emerging mobility options also positively influence the participation levels in the other. This is intuitive since households with sustainability-oriented attitudinal predispositions are likely to have higher affinities towards using CS and RH services (Acheampong and Siiba 2020, Azimi et al. 2021). Despite this overall positive association, the stochastic dependence between the two shared mobility services was characterized by nonlinearity – stronger dependence in the left tail (lower participation levels in the two programs) and relatively weaker dependence in the right tail (higher participation levels in the two programs) of the bivariate distribution (Figure 5). This is in line with the descriptive insights presented earlier (Figure 2). Technology-savvy or high-income individuals may be more likely to use ride-hailing services given their higher value of time. At the same time, they could be less likely to use carsharing since they would want to spend their time more productively by not driving themselves. The statistically significant nonlinear stochastic dependence is observed even after accounting for several key behavioral and sociodemographic factors. These results demonstrate the effectiveness of the proposed methodological framework to understand complex interrelationships more accurately and better predict the impacts of emerging shared mobility technologies.

To better interpret the findings on exogenous factors predicting CS and RH use, we compute marginal effects that show the effects of a change in exogenous variable on the marginal probabilities of participation levels in CS and RH programs. Given the joint discrete ordered framework, we also compute joint marginal effects – showing the effects of exogenous variables on the joint probability of a household having specific participation levels in carsharing and ride-hailing programs (Table 6). The marginal effects in Table 6 are on a probability scale; the percent increase or decrease can be obtained by multiplying the marginal effects by 100.

5.1. Transit Use, Housing, & Parking Costs

Households with greater one-way transit trips per member were more likely to currently participate in CS and RH programs (Table 5). A ten-unit (trips) increase in average one-way transit trips per member was correlated with a 6.2% increase in the likelihood of currently using RH programs (Table 6). Transit use was also predictive of the likelihood that a household would use both CS and RH programs (Table 6). A ten-unit increase in transit trips was associated with a 3.6% increase in the likelihood of a household currently using CS as well as RH services (Table 6). These findings are intuitive since RH and CS programs can provide first- and last-mile connectivity to those who are either heavily dependent on transit or prefer to use transit (Shaheen and Chan 2016, Zhang and Zhang 2018). Our findings suggest that a more efficient transportation system can be created by realizing the synergy between transit and shared mobility services. Our findings are in agreement with past studies indicating a positive relationship between public transit and the use of carsharing or ride-hailing services (Ceccato and Diana 2021, Loa and Habib 2021, Tian et al. 2023). However, we note that the relationship between shared mobility and transit use is complicated and driven by contextual factors, with studies also showing a substitutive relationship between the two (Barajas and Brown 2021, Wali et al. 2022, Wang et al. 2022, Qiao and Yeh 2023) – especially with regards to the key role of the built environment of where people live and work (Wali et al. 2022). To this end, future studies should jointly examine the demand for shared mobility services while incorporating built environment characteristics and its potential interactions with activity patterns and active travel.

Those who pay to park at their residences are more likely to use CS and RH programs (Table 5 and 6). Greater amount paid for parking is also correlated with a higher likelihood of households currently using CS and RH programs. A ten-dollar increase in the amount paid for parking is associated with a 0.4% and 0.1% increase in the marginal likelihood of a household currently using RH and CS programs, respectively (see individual marginal effects in Table 6) – and a 0.4% reduction in the joint probability of a household not interested (lowest levels) in both RH and CS programs (Table 6). Availability of parking for private cars has been decreasing (especially in urban areas) (Soltani et al. 2021). Parking stress is among the key reasons users choose not to drive (Henao and Marshall 2019, Wadud 2020), and individuals are more likely to use carsharing or ride-hailing when the out-of-pocket parking costs increase even slightly (Jacobson and King 2009, Sarriera et al. 2017).

5.2. (Electric) Vehicle Ownership & Commuting

Households who own plug-in electric vehicles (PEVs) are statistically significantly more likely to currently use RH services. Compared to those who do not own PEVs, the likelihood of a household currently using RH increased by around 1.4 percentage points with each additional PEV (Table 6). The likelihood of a household not interested in both RH and CS programs also reduced by 1.1% with each additional PEV. Note that while PEV ownership variable was not included (statistically insignificant) in the equation for CS use (i.e., no direct effect), we are still able to predict the indirect effect of PEV ownership on CS use by virtue of the joint modeling framework. The above finding is expected since households with electric vehicles are more likely to exhibit sustainable attitudinal predispositions and thus relatively more receptive to other emerging technologies as well. Electric vehicles and shared mobility are two of the four key pillars (connectivity, automation, sharing, and electrification) of future smart cities (Mahdavian et al. 2021). Evidence suggests that individuals with self-expression values, positive attitudes towards novelties, and environmentally friendly attitudes or behaviors are more likely to possess positive opinions about connected, automated, shared, and electric vehicle systems (Wu et al. 2020). From a policy standpoint, the above findings highlight the synergies between shared consumption and transportation electrification and suggest that incentives that promote the adoption of clean (electric) transportation may also further accelerate the adoption of RH and CS services over time. Those households with greater one-way commute distance per commuter were more likely to currently use CS programs (Table 5). A ten-mile increase in one-way commute was correlated with a 0.23% increase in the likelihood of currently using CS programs (Table 6). This variable was not statistically significant in the equation for RH use. Greater number of household vehicles was negatively correlated with participation in CS programs. This finding is in line with previous studies suggesting a negative association between CS membership and vehicle holdings (Martin et al. 2010, Dias et al. 2017, Wu et al. 2020). Likewise, each additional frequent driver in a household was correlated with a 2.3% and 0.9% decrease in the likelihood of currently participating in RH and CS programs, respectively (Table 6). Interestingly, compared to RH, the negative effect of frequent drivers in a household on the use of CS was less pronounced (Table 5).

5.3.Awareness & Concerns

Awareness about RH programs was positively correlated with the likelihood of a household using ride-hailing programs. Compared to households who were aware of RH programs, those who were not on-average had a 9.2% decrease in the likelihood of currently participating in RH programs (Table 6). Consumer awareness has been a key factor predicting adoption of technology in general (Bharati and Chaudhury 2006) and shared mobility services in particular (Circella et al. 2018, Wang et al. 2020). Likewise, those who feel RH programs are too expensive or unaffordable were significantly less likely to currently use ride-hailing and significantly more likely to report no interest in ride-hailing programs (Table 6). Note that while the awareness and concern related variables were statistically insignificant in the equation for carsharing use, the joint modeling framework captures the indirect effect of these variables on the joint distribution of RH and CS use (Table 6). The relatively stronger impact of the awareness variable suggests that interventions to increase consumer awareness of shared mobility services continue to be an effective strategy to promote such services. Programs that convey the benefits of collaborative consumption can enhance environmental awareness of the general population supporting further adoption of shared mobility services. Further, unaffordability remains a key barrier to RH adoption especially by the low-income individuals (Qiao and Yeh 2023). Our findings suggest that incentives that improve affordability of shared mobility services can increase adoption of RH services in population groups that may need such services the most. This is especially relevant because RH services have the potential to serve as an alternative transportation mode in low income and more vulnerable neighborhoods (Li et al. 2022). However, prevalence of RH use remains low among residents of low-density and low-income neighborhoods (Liu et al. 2020, Li et al. 2022). Thus, interventions that can improve RH affordability and general awareness could help ameliorate the social inequalities in the spatial distribution of shared mobility services.

5.4.Demographic & Socioeconomic Factors

Statistically significant correlations are found for a host of sociodemographic factors. Households with greater members and greater number of members with postgraduate degrees were more likely to currently use CS and RH programs. Contrarily, households with a greater number of members with lower education were more likely to report no interest in CS and RH programs (see (joint) marginal effects in Table 6). Greater number of females and fulltime workers was associated with higher likelihoods of using CS and/or RH services. A statistically significant interaction effect was also observed between number of females and fulltime workers in relation to the use of RH services (see Table 5). As expected, households with a greater number of retired individuals were significantly less likely to use RH and CS services. This finding may be tracing the relatively lower technological awareness of older individuals compared to younger individuals. Importantly, the result implies that old age continues to be a barrier to the adoption of shared mobility services at times when older individuals may benefit the most from the use of shared mobility, especially ride-hailing services (Talmage et al. 2021). With the number of seniors (aged 65 or above) in the U.S. doubling in the next 30 years, programs that enhance the technological awareness of an aging population and demonstrate the benefits of shared mobility (e.g., greater accessibility) can accelerate the adoption of such services by older individuals. A greater number of full-time students in a household was associated with a higher likelihood of using RH services. Compared to low-income households, an incrementally increasing non-linear effect was observed for high income households in terms of their greater propensity to use RH services. The income variable was found statistically insignificant in the equation for CS use.

Table 5. Estimation Results for Participation Levels in CS and RH Programs: Standard Gaussian-, Clayton Copula-, and Best-Fit Clayton Copula with Heterogeneous Mixtures-Based Bivariate Ordered Probit Models.

Category	Variables	Gaussian Copula Based Bivariate Ordered Probit Model				Clayton Copula Based Bivariate Ordered Probit Model				Best-Fit Clayton Copula with Heterogeneous Mixtures Based Bivariate Ordered Probit Model			
		RH Use		CS Use		RH Use		CS Use		RH Use		CS Use	
		β	t-stat	β	t-stat	β	t-stat	β	t-stat	β	t-stat	β	t-stat
Awareness & Concerns	Not aware of ride-hail/carshare programs	-0.487	-8.11	---	---	-0.435	-7.84	---	---	-0.425	-7.36	---	---
	Too expensive/unaffordable	-0.359	-6.86	---	---	-0.298	-6.4	---	---	-0.285	-6.45	---	---
Transit Use, Parking, Housing	Average one-way transit trips per member	0.019	2.37	0.033	3.3	0.023	2.91	0.035	3.45	0.022	2.82	0.034	3.3
	Pay to park at residence	0.212	2.25	0.473	4.34	0.245	3.1	0.492	4.71	0.229	3.13	0.393	3.84
	Amount paid to park	0.002	3.92	0.002	5.1	0.002	3.05	0.001	4.14	0.001	2.59	0.001	2.6
	Parking type: personal garage	-0.046	-1.69	---	---	-0.034	-1.26	---	---	-0.032	-1.61	---	---
	Housing: Apartment	0.171	4.35	0.123	1.78	0.143	4.38	0.096	1.62	0.139	5.16	0.088	1.59
(Electric) Vehicle Ownership & Commute Distance	Number of plug-in electric vehicles (PEVs)	0.052	2.79	---	---	0.050	2.98	---	---	0.052	3.17	---	---
	Number of household vehicles	---	---	-0.055	-2.1	---	---	-0.057	-1.9	---	---	-0.039	-1.8
	Average one-way commute distance per commuter in household	---	---	0.002	4.8	---	---	0.003	4.87	---	---	0.002	3.76
	Missing commute distance dummy	---	---	0.163	2.05	---	---	0.147	2.16	---	---	0.112	2.21
	Number of frequent drivers in household	-0.068	-2.3	-0.083	-2.31	-0.089	-3.91	-0.093	-2.64	-0.090	-4.07	-0.085	-3.52
Socio demographic Factors	Number of household members	0.062	2.34	0.190	6.43	0.087	3.38	0.198	6.58	0.084	3.8	0.174	5.76
	Number of members with postgraduate degrees	0.061	2.62	0.079	2.23	0.050	2.3	0.076	1.98	0.042	1.83	0.049	2.07
	Number of members with some college education	-0.101	-4.29	-0.071	-1.63	-0.098	-4.63	-0.061	-1.36	-0.098	-4.39	-0.055	-1.44
	Number of females	0.128	2.77	0.040	1.61	0.119	3.1	0.018	0.88	0.116	2.98	0.007	0.47

Notes: (---) indicates Not Applicable; Participation levels in carsharing (CS) and ride-hailing (RH) each recorded on five-point ordinal scale.

Table 5. (Continued). Estimation Results for Participation Levels in CS and RH Programs: Standard Gaussian-, Clayton Copula-, and Best-Fit Clayton Copula with Heterogeneous Mixtures-Based Bivariate Ordered Probit Models.

Category	Variables	Gaussian Copula Based Bivariate Ordered Probit Model				Clayton Copula Based Bivariate Ordered Probit Model				Best-Fit Clayton Copula with Heterogeneous Mixtures Based Bivariate Ordered Probit Model			
		RH Use		CS Use		RH Use		CS Use		RH Use		CS Use	
		β	t-stat	β	t-stat	β	t-stat	β	t-stat	β	t-stat	β	t-stat
Sociodemographic Factors	Number of fulltime workers	0.092	2.14	---	---	0.111	3.26	---	---	0.111	3.34	---	---
	Number of females × fulltime workers	-0.031	-1.79	---	---	-0.040	-2.16	---	---	-0.040	-2.06	---	---
	Number of retired individuals	-0.275	-10.51	-0.278	-11.27	-0.270	-9.93	-0.264	-11.85	-0.265	-9.67	-0.216	-6.23
	Number of fulltime students	0.160	3.75	---	---	0.163	4.28	---	---	0.168	4.34	---	---
	Income: Less than $50,000 (base)	---	---	---	---	---	---	---	---	---	---	---	---
	Income: $50,000 to $74,999	0.078	1.27	---	---	0.083	1.57	---	---	0.082	1.51	---	---
	Income: $75,000 to $99,999	0.171	4.07	---	---	0.144	3.43	---	---	0.144	3.5	---	---
	Income: $100,000 to $149,999	0.155	3.39	---	---	0.138	3.51	---	---	0.136	3.44	---	---
	Income: $150,000 or more	0.289	7.42	---	---	0.253	6.8	---	---	0.252	6.47	---	---

Notes: (---) indicates Not Applicable; Participation levels in carsharing (CS) and ride-hailing (RH) each recorded on five-point ordinal scale.

Table 6. Marginal and Joint Marginal Effects from Best-Fit Clayton Copula Finite Mixture Bivariate Ordered Probit Model for Participation Levels in CS and RH Programs.

Category	Variables	Best-Fit Clayton Copula with Heterogeneous Mixtures Based Bivariate Ordered Probit Model											
		RH Use					CS Use					Joint Marginal Effects: RH & CS	
		[1]	[2]	[3]	[4]	[5]	[1]	[2]	[3]	[4]	[5]	RH [5] & CS [5]	RH [1] & CS [1]
Awareness & Concerns	Not aware of ride-hail/carshare programs	0.157	-0.017	-0.010	-0.039	-0.092	----	----	----	----	----	-0.008	0.083
	Too expensive/unaffordable	0.105	-0.008	-0.006	-0.025	-0.066	----	----	----	----	----	-0.005	0.058
Transit Use, Parking, Housing	Average one-way transit trips per member (in 10s)	-0.076	-0.004	0.003	0.016	0.062	-0.123	-0.007	0.020	0.048	0.062	0.036	-0.077
	Pay to park at residence	-0.080	-0.004	0.003	0.017	0.064	-0.139	-0.012	0.023	0.057	0.071	0.040	-0.084
	Amount paid to park (in 10s of USD)	-0.005	0.000	0.000	0.001	0.004	-0.003	0.001	0.001	0.001	0.001	0.001	-0.004
	Parking type: personal garage	0.011	0.000	-0.001	-0.003	-0.008	----	----	----	----	----	-0.001	0.007
	Housing: Apartment	-0.050	-0.001	0.002	0.011	0.037	-0.035	0.006	0.006	0.012	0.011	0.008	-0.039
(Electric) Vehicle Ownership & Commute Distance	Number of plug-in electric vehicles (PEVs)	-0.019	0.000	0.001	0.004	0.014	----	----	----	----	----	0.001	-0.011
	Number of household vehicles	----	----	----	----	----	0.016	-0.004	-0.003	-0.005	-0.004	-0.002	0.005
	Average one-way commute distance per commuter in household (in 10s of miles)	----	----	----	----	----	-0.008	0.002	0.001	0.002	0.002	0.001	-0.002
	Missing commute distance dummy	----	----	----	----	----	-0.044	0.008	0.007	0.014	0.014	0.007	-0.013
	Number of frequent drivers in household	0.033	-0.001	-0.002	-0.008	-0.023	0.035	-0.010	-0.006	-0.010	-0.009	-0.006	0.030

Notes: RH is ride-hailing; CS is carsharing; Levels of RH and CS use: 1 - not interested; 2 is might participate someday; 3 is not participated in the past, but plan to participate; 4 is participated in the past, but not now; 5 is currently participates. Some cells may contain '0.000' due to three digits rounding; % increase/decrease can be obtained by multiplying the marginal effects by 100. (---) indicates Not Applicable.

Table 6. (Continued). Marginal and Joint Marginal Effects from Best-Fit Clayton Copula Finite Mixture Bivariate Ordered Probit Model for Participation Levels in Carsharing and Ridesharing Programs.

Category	Variables	Best-Fit Clayton Copula with Heterogeneous Mixtures Based Bivariate Ordered Probit Model											
		RH Use					CS Use					Joint Marginal Effects: RH & CS	
		[1]	[2]	[3]	[4]	[5]	[1]	[2]	[3]	[4]	[5]	RS [5] & CS [5]	RS [1] & CS [1]
Sociodemographic Factors	Number of household members	-0.030	-0.001	0.001	0.007	0.022	-0.066	0.005	0.011	0.024	0.026	0.014	-0.036
	Number of members with postgraduate degrees	-0.015	0.000	0.001	0.003	0.011	-0.019	0.003	0.003	0.006	0.006	0.004	-0.014
	Number of members with some college education	0.036	-0.001	-0.002	-0.008	-0.024	0.022	-0.006	-0.004	-0.007	-0.006	-0.004	0.028
	Number of females	-0.029	0.001	0.001	0.007	0.020	-0.003	0.001	0.000	0.001	0.001	0.002	-0.018
	Number of fulltime workers	-0.024	0.000	0.001	0.005	0.018	----	----	----	----	----	0.001	-0.015
	Number of retired individuals	0.098	-0.007	-0.005	-0.024	-0.061	0.091	-0.033	-0.014	-0.024	-0.019	-0.012	0.088
	Number of fulltime students	-0.059	-0.002	0.002	0.013	0.046	----	----	----	----	----	0.003	-0.036
	Income: Less than $50,000 (base)	----	----	----	----	----	----	----	----	----	----	----	----
	Income: $50,000 to $74,999	-0.029	0.000	0.001	0.006	0.022	----	----	----	----	----	0.002	-0.017
	Income: $75,000 to $99,999	-0.051	-0.001	0.002	0.011	0.039	----	----	----	----	----	0.003	-0.031
	Income: $100,000 to $149,999	-0.048	-0.001	0.002	0.011	0.036	----	----	----	----	----	0.003	-0.029
	Income: $150,000 or more	-0.088	-0.004	0.003	0.019	0.069	----	----	----	----	----	0.005	-0.055

Notes: RH is ride-hailing; CS is carsharing; Levels of RH and CS use: 1 - not interested; 2 is might participate someday; 3 is not participated in the past, but plan to participate; 4 is participated in the past, but not now; 5 is currently participates. Some cells may contain ‘0.000’ due to three digits rounding; % increase/decrease can be obtained by multiplying the marginal effects by 100. (----) indicates Not Applicable.

5.5.Treatment Effects and Policy Implications

To further elaborate the policy implications of our results, we conducted a simulation exercise to compute Average Treatment Effects for the best-fit Clayton copula-based finite mixture joint model. Treatment effects were also computed for the independent models to examine what would be obtained if the two decisions (carsharing and ride-hailing use) were treated independently. While treatment effects typically arise in causal and/or counterfactual frameworks (Heckman and Vytlacil 2001, Heckman et al. 2014), we use the term treatment effects below to be consistent with terminology in transport applications (Nair et al. 2018, Kang et al. 2021, Wali and Khattak 2022). Depending on the type of treatment, two different methods were used to measure treatment effects. For a dichotomous variable (e.g., user awareness of shared mobility services), the two treatment states assume if all people are not aware of shared mobility services vs. all people aware of such services. For a continuous variable (e.g., average transit trips per individual), the base case refers to the number of existing transit trips, whereas the treated case refers to increasing the number of existing transit trips by ten units. For each of the two states, marginal predictions of carsharing and ride-hailing use probabilities are computed[7]. The difference between the two sets of individual-level probabilities multiplied by 100 results in an average treatment effect.

Results are shown in Table 7. The direction of the average treatment effects from the independent model and the best-fit copula-based finite mixture model is consistent with each other and with the discussion in the previous section. However, there are meaningful differences in the magnitudes of the estimated average treatment effects implied by the two models. For example, if the individual was not aware of shared mobility services, the likelihood of being not interested in ride-hailing increased by 15.7% - compared to a 13.1% increase implied by the independent model. This difference translates to a 19.6% change between the average treatment effects of the independent model and the best-fit model (Table 7). Likewise, those who felt ridesharing programs were too expensive had a 10.4% and 4.5% increase in the likelihood of not being interested in ride-hailing in the best-fit and independent models, respectively. This translates to a 133% change between the average treatment effects implied by the simplistic independent and best-fit model (Table 7). Related to parking availability, individuals who paid to park at their residence had on-average a 13.9% decrease in likelihood of not being interested in carsharing programs. In comparison, the independent model overestimated the impact of paid parking, suggesting a 18.2% decrease in the likelihood of not being interested in carsharing programs. Overall, the differences (in terms of percent change) in average treatment effects for different exogenous factors in ride-hailing outcome ranged between -86.6% and 133% between the independent and the best-fit model, that incorporated the behavioral heterogeneity and potential dependence between car sharing and ride-hailing use. For carsharing outcome, the differences in treatment effects between the two modeling frameworks ranged between -47.5% and 80.8% across different variables (Table 7).

Collectively, these differences highlight the potential of considerable misestimation of average treatment effects if behavioral heterogeneity and non-linear joint dependence between carsharing and ride-hailing use are ignored. To assess the impacts of shared mobility services on travel demand more fully, travel demand forecasting models should consider the heterogeneous dependence between carsharing and ride-hailing use patterns, as suggested by the statistically significant non-linear dependence (even after controlling for a variety of demographic and behavioral factors) found in this study. Our results demonstrate the usefulness of the modeling framework in providing deeper insights on the complex stochastic dependence patterns between ride-hailing and carsharing use patterns. Besides the conceptual and policy insights discussed, the fusion of finite mixture modeling methods with the copula-based joint discrete choice framework was also clearly supported by model goodness of fit metrics.

[7] For brevity, we only compute the marginal treatment effects on the likelihood of the first level (Not Interested) of carsharing and ride-hailing use. Likewise, joint treatment effects were not computed. The joint marginal effects for the best-fit finite mixture Clayton copula-based model were shown and discussed in Table 6.

Table 7. Estimated Treatment Effects Across the Base Model (Independent Models) & Best-Fit Heterogeneous Copula Model.

Variables	Base Level	Treatment Level	Independent Models[a]		Best-Fit Heterogeneous Copula Model[b]		% Change[1]	
			RH [1]	CS [1]	RH [1]	CS [1]	RH [1]	CS [1]
Awareness & Concerns								
Not aware of ride-hail/carshare programs	Aware	Not aware	13.16	----	15.74	----	19.6	----
Too expensive/unaffordable	Affordable	Unaffordable	4.50	----	10.49	----	133.0	----
Transit Use, Parking & Housing								
Average one-way transit trips per member (in 10s)	Existing one-way transit trips	10 unit (trips) increase	-5.70	-12.03	-7.63	-12.29	-33.9	-2.2
Pay to park at residence	Not paying	Paying	-6.67	-18.29	-7.98	-13.93	-19.6	23.8
Amount paid to park (in 10s of USD)	Existing parking amount	One SD increase	-2.41	-1.89	-1.68	-1.14	30.2	39.6
Parking type: personal garage	Other	Personal garage	2.34	----	1.14	----	-51.3	----
Housing: Apartment	Other	Apartment	-5.43	-4.04	-4.96	-3.50	8.6	13.3
(Electric) Vehicle Ownership & Commute Distance								
Number of plug-in electric vehicles (PEVs)	Existing # of …	One unit increase	-2.26	----	-1.85	----	17.9	----
Number of household vehicles	Existing # of …	One unit increase	----	3.06	----	1.61	----	-47.5
Average one-way commute distance per commuter in household (in 10s of miles)	Existing distance	One SD increase	----	-2.43	----	-1.43	----	41.1
Number of frequent drivers in household	Existing # of …	One unit increase	----	3.04	----	3.51	----	15.6
Sociodemographic Factors								
Number of household members	Existing # of …	One unit increase	-1.59	-7.18	-2.97	-6.62	-86.6	7.8
Number of members with postgraduate degrees	Existing # of …	One unit increase	-2.15	-3.08	-1.51	-1.93	30.0	37.4
Number of members with some college education	Existing # of …	One unit increase	3.97	2.57	3.55	2.23	-10.6	-13.3
Number of females	Existing # of …	One unit increase	-3.57	-1.39	-2.89	-0.27	18.9	80.9

Notes: RH is ride-hailing; CS is carsharing; Levels of RH and CS use: 1 - not interested. (----) indicates Not Applicable. (a) and (b): Numbers in the columns show the % increase or decrease in the likelihood of observing 'not interested' level for ride-hailing and carsharing outcomes, respectively. The last two columns show the percent change between the treatment effects under the independent and the best-fit heterogeneous copula models. % change between ride-hailing and carsharing treatment effects calculated as [(RH [1] $_{\text{BEST-FIT MODEL}}$ - RH [1] $_{\text{INDEPENDENT MODEL}}$) / | RH [1] $_{\text{INDEPENDENT MODEL}}$ |) × 100] and [(CS [1] $_{\text{BEST-FIT MODEL}}$ - CS [1] $_{\text{INDEPENDENT MODEL}}$) / | CS [1] $_{\text{INDEPENDENT MODEL}}$ |) × 100], respectively.

Table 7. (Continued). Estimated Treatment Effects Across the Base Model (Independent Models) & Best-Fit Heterogeneous Copula Model.

Variables	Base Level	Treatment Level	Independent Models[a]		Best-Fit Heterogeneous Copula Model[b]		% Change[1]	
			RH [1]	CS [1]	RH [1]	CS [1]	RH [1]	CS [1]
Number of fulltime workers	Existing # of …	One unit increase	-3.13	----	-2.45	----	21.9	----
Number of retired individuals	Existing # of …	One unit increase	9.43	9.55	9.77	9.12	3.5	-4.6
Number of fulltime students	Existing # of …	One unit increase	-10.22	----	-5.86	----	42.7	----
Income: \$50,000 to \$74,999	Less than \$50,000	\$50,000 to \$74,999	-3.22	----	-2.91	----	9.8	----
Income: \$75,000 to \$99,999	Less than \$50,000	\$75,000 to \$99,999	-6.13	----	-5.10	----	16.8	----
Income: \$100,000 to \$149,999	Less than \$50,000	\$100,000 to \$149,999	-6.42	----	-4.81	----	25.1	----
Income: \$150,000 or more	Less than \$50,000	\$150,000 or more	-10.07	----	-8.84	----	12.2	----

Notes: RH is ride-hailing; CS is carsharing; Levels of RH and CS use: 1 - not interested. (----) indicates Not Applicable. (a) and (b): Numbers in the columns show the % increase or decrease in the likelihood of observing 'not interested' level for ride-hailing and carsharing outcomes, respectively. The last two columns show the percent change between the treatment effects under the independent and the best-fit heterogeneous copula models. % change between ride-hailing and carsharing treatment effects calculated as [(RH [1] $_{\text{BEST-FIT MODEL}}$ - RH [1] $_{\text{INDEPENDENT MODEL}}$) / | RH [1] $_{\text{INDEPENDENT MODEL}}$ |) × 100] and [(CS [1] $_{\text{BEST-FIT MODEL}}$ - CS [1] $_{\text{INDEPENDENT MODEL}}$) / | CS [1] $_{\text{INDEPENDENT MODEL}}$ |) × 100], respectively.

6. LIMITATIONS

The 2017 California Vehicle Survey represents a solid source of representative data enabling a deeper understanding of CS and RH users. However, the study results are likely conservative as the survey is slightly outdated and may not reflect the latest trends in the use of shared mobility services. The uniqueness of California in several aspects could limit the generalizability of the empirical findings presented herein. Like most other relevant studies, the data used in this study are self-reported by the consumers and may suffer from recall bias. The study findings capture pre-COVID travel patterns and behaviors, and do not reflect the significant travel behavior alterations observed during the COVID-19 pandemic. As discussed, the results are expected to reflect the post-pandemic travel behaviors though as history shows that individual travel patterns and behaviors eventually reach a balance over time. The dependent variables presented in the study are collected at the household-level since the California Energy Commission forecasting model operates at a household level. However, the decisions to use CS and RH are likely more personal in nature. To this end, the results in this study can be deemed as conservative estimates of the consumers' use of the two disruptive shared mobility options. Serving a different purpose, the proposed model is different from a traditional person-level mode choice model with choice-specific attributes (time, cost, etc.). From an application standpoint, the proposed model can be used to forecast more aggregate use patterns of CS and RH services incorporating a broad spectrum of policy-relevant behavioral factors and capturing the unobserved stochastic dependence contours driving the use of such services. Future studies can benefit from simultaneously analyzing participation levels in CS and RH programs at a more microscopic level, e.g., at a level of a trip or tour. The present study unveiled complex nonlinear correlations between the usage levels of carsharing and ride-hailing programs. Future research can extend the copula-based finite mixture joint behavioral model to also incorporate potential correlations within each mode – in addition to the nonlinear correlations between the two modes captured in this study. Finally, future studies should incorporate built environment and land use measures to further enhance the descriptive capability of the models. We were unable to do so as residential addresses (or block group locations) are not publicly available in the California Vehicle Survey.

7. CONCLUSIONS

Driven by rapid advancements in information and communication technologies, consumers' attitudes and preferences towards service consumption have markedly evolved in the last decade – with a shift to distributed and collaborative (as opposed to centralized) consumption. The concept of collaborative consumption has led to new mobility-on-demand services – providing more flexible, accessible, and convenient mobility options. Among them, ride-hailing (on-demand ride services) and latest ICT-driven forms of car-sharing have emerged as the key mobility-on-demand services. One of the key necessary elements to accurately forecast the potential impacts of the two disruptive technologies is to gain an in-depth understanding of the behavioral and sociodemographic predictors of carsharing and ride-hailing use. To this end, the present study contributed by jointly analyzing consumers' participation levels in carsharing (CS) and ride-hailing (RH) programs. Using comprehensive data from the California Vehicle Survey, rigorous finite mixture based elliptical/Archimedean copula based bivariate ordered probit (BOP) models were developed to explore how policy sensitive behavioral factors correlate with households' participation levels in CS and RH programs. Two important methodological issues were simultaneously analyzed: the extent and nature of stochastic dependence between consumers' use of RH and CS services and heterogeneity in latent factors associated with the consumers' use of these two disruptive technologies.

Among the elliptical and Archimedean copula based joint models considered, finite mixture Clayton copula-based BOP model resulted in best-fit. Even after accounting for a host of behavioral and sociodemographic factors, a nonlinear stochastic dependence pattern between CS and RH use was observed. Despite an overall positive association (Kendall's τ of 0.401), we found a relatively stronger dependence in the left tail (lower participation levels in the two programs) and a relatively weaker dependence in the right tail (higher participation levels in the two programs) of the bivariate distribution characterizing the dependencies between the latent factors influencing consumers' use of CS and RH services. Behaviorally, this implied that households who have lower participation levels in one of the programs are more likely to have lower participation level in the other shared mobility program as well. However, households who have high participation levels in one of the programs (e.g., ride-hailing) are relatively less likely to also have high participation levels in carsharing. Important behavioral implications of these findings were discussed in terms of the synergistic as well as competing relationships between the two emerging shared mobility options.

Regarding behavioral factors, households with greater one-way transit trips per member were more likely to currently participate in CS and RH programs. Likewise, if households paid to park at their residences, they were more likely to use CS and RH programs. Compared to those who do not own plug-in electric vehicles (PEV), the likelihood of a household currently using RH increased by around 1.37 percentage points with each additional PEV. Households with greater one-way commute distance per commuter were more likely to currently use CS programs. Interestingly, compared to ride-hailing, the negative effect of frequent drivers in a household on carsharing use was less pronounced. A host of sociodemographic factors were independently associated both with the use of CS as well as RH services.

The study discussed the practical implications of the findings. Beyond sociodemographic factors, the study provides a more granular understanding of key behavioral factors related to the use of CS and RH programs. By reflecting the use patterns of two disruptive shared mobility services, the findings may inform more accurate travel forecasts for general planning and programming purposes. From a travel demand and forecasting perspective, the behavioral factors considered in this study can inform creation of *"what-if"* scenarios to better understand the aggregate use patterns of such technologies by different sociodemographic groups in the population. To this end, capturing the synergistic and competing relationships between CS and RH (as is done in the present study) can lead to more realistic future alternative scenarios.

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9. AUTHOR CONTRIBUTIONS

The author confirms contribution to the paper as follows. Conceptualization & Study Design, Methodology, Data Curation, Analysis, Investigation, Interpretation of Results, Writing – Original draft preparation, Writing – revised paper preparation, Project Administration: **B Wali.**

10. APPENDIX A

Here, we present a detailed exposition of the copula-based finite mixture joint modeling framework adopted in this study. An ordered discrete outcome modeling framework is employed since the two response outcomes, namely households' levels of participation in carsharing (CS) and ride-hailing (RH) programs, are each recorded as on a five-point scale with ordinal nature[8]. At a basic level, univariate ordered probit models can be used to independently model the two response outcomes. However, given the dependencies between the two response outcomes highlighted in section 3.1, a joint discrete outcome estimation framework that can model the joint probability distribution of participation levels in CS and RH programs will lead to more efficient parameter estimates. Using matrix notation, the likelihood function of the bivariate ordered probit model can be derived as follows. Considering Q as an index for households (indexed from 1 through Q), the participation levels of the households in CS and RH programs are represented by l_K (where $K = 1$ and 2 for carsharing and ride-hailing, respectively) - with the following range of values: not interested in participating (l_K=1), might participate someday ($l_K = 2$), not participated in the past but plan to participate ($l_K = 3$), have participated in the past, but am not currently participating $l_K = 4$), and currently participates ($l_K = 5$). The latent and observed participation levels in CS and RH programs are represented by two $Q \times 2$ matrices, namely $y^*_{l_K}$ and y_{l_K}, respectively. To map the latent participation levels to the observed counterparts, a vector of estimable thresholds (Θ_{l_K}) can be used. Contained in $y^*_{l_K}$, the latent participation levels in CS and RH programs are modeled as a function of independent variables and unobserved/latent factors (Greene and Hensher 2010):

$$y_{Ql_K}{}^* = \beta_{l_K}{}'\boldsymbol{x}_{Ql_K} + \aleph_{Ql_K} \qquad (1)$$

[8] The response categories broadly represent an increasing level of usage (e.g., not interested, planning to participate in future, previous but no current participation, and current participation). Thus, we considered it appropriate to treat the participation levels as ordered response outcomes. We note that the outcomes are not perfectly ordered – a common issue in survey data. Ordered models have been used in the past to model categorical variables exhibiting some potential ambiguity (Barbour et al. 2020, Du et al. 2020) or potential overlap and imperfect ordering across categories (Gomez et al. 2021). Future studies should explore unordered discrete choice models to jointly model participation levels in carsharing and ride-hailing programs.

Where: $\beta_{l_K}{}'$ represents the outcome-specific vector of estimable coefficients/parameter estimates for unique (or common) independent variables in the latent propensity equations for participation levels in CS and RH programs. The residuals/unobserved factors associated with the two discrete ordered response outcomes are captured in the vector $\aleph_{Q_{l_K}}$ (Quddus et al. 2002, Greene and Hensher 2010). Using the estimable thresholds, the following mapping function is then used to map observed participation levels with the latent participation levels in CS and RH programs (Greene and Hensher 2010):

$$y_{l_K Q} = l_K \text{ if } \Theta_{l_K-1} < y_{Q l_K}{}^* < \Theta_{l_K} \tag{2}$$

Substituting Eq. (2) in Eq. (1) provides an expression for observed participation levels in CS and RH programs in terms of predictors of the latent participation levels:

$$y_{l_K Q} = l_K \text{ if } \Theta_{l_K-1} < \beta_{l_K}{}'\boldsymbol{x}_{Q_{l_K}} + \aleph_{Q_{l_K}} < \Theta_{l_K} \tag{3}$$

$$y_{l_K Q} = l_K \text{ if} \left(\Theta_{l_K-1} - \beta_{l_K}{}'\boldsymbol{x}_{Q_{l_K}} \right) < \aleph_{Q_{l_K}} < (\Theta_{l_K} - \beta_{l_K}{}'\boldsymbol{x}_{Q_{l_K}}) \tag{4}$$

To arrive at a joint bivariate discrete outcome ordered model, the mathematical formulation in Eq. (3) and Eq. (4) is expanded by specifying the classic textbook joint functional form for the unobservables ($\aleph_{Q_1}$ and $\aleph_{Q_2}$) associated with the participation levels in CS and RH programs – namely a bivariate normal distribution (Greene and Hensher 2010), $\begin{pmatrix} \aleph_{Q_{l_K}=1} \\ \aleph_{Q_{l_K}=2} \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right]$. Using the system of equations, the joint probability that a household exhibits a participation level l_1 in CS and l_2 in RH program is derived as (Ferdous et al. 2010, Greene and Hensher 2010):

$$\begin{aligned} P\left(y_{Q_1} = l_1, y_{Q_2} = l_2\right) \\ = P\left(\left[\left(\Theta_{l_1-1} - \beta_1{}'\boldsymbol{x}_{Q_1}\right) < \aleph_{Q_1} < \left(\Theta_{l_1} - \beta_1{}'\boldsymbol{x}_{Q_1}\right)\right], \left(\Theta_{l_2-1} - \beta_1{}'\boldsymbol{x}_{Q_2}\right) < \aleph_{Q_2} \right. \\ \left. < \left(\Theta_{l_2} - \beta_1{}'\boldsymbol{x}_{Q_2}\right)\right) \end{aligned} \tag{5}$$

$$= P\left[\aleph_{Q_1} < \left(\Theta_{l_1} - \beta_1{}'\boldsymbol{x}_{Q_1}\right), \aleph_{Q_2} < \left(\Theta_{l_2} - \beta_2{}'\boldsymbol{x}_{Q_2}\right)\right] - P\left[\aleph_{Q_1} < \left(\Theta_{l_1} - \beta_1{}'\boldsymbol{x}_{Q_1}\right), \aleph_{Q_2} < \left(\Theta_{l_2-1} - \beta_2{}'\boldsymbol{x}_{Q_2}\right)\right] - P\left[\aleph_{Q_1} < \left(\Theta_{l_1-1} - \beta_1{}'\boldsymbol{x}_{Q_1}\right), \aleph_{Q_2} < \left(\Theta_{l_2} - \beta_2{}'\boldsymbol{x}_{Q_2}\right)\right] + P\left[\aleph_{Q_1} < \left(\Theta_{l_1-1} - \beta_1{}'\boldsymbol{x}_{Q_1}\right), \aleph_{Q_2} < \left(\Theta_{l_2-1} - \beta_2{}'\boldsymbol{x}_{Q_2}\right)\right]$$

The exposition presented above jointly models the household's participation levels in CS and RH programs. In particular, it takes into account the potential interrelationships between the two response outcomes arising due to common observed and/or unobserved factors. The strength of the interrelationship is determined by the estimable correlation parameter ρ, that governs the degree of dependence between $\aleph_{Q_{l_K}=1}$ and $\aleph_{Q_{l_K}=2}$ after the system of equations is conditioned on observed explanatory variables. Compared to independent ordered probit models, the joint model presented above leads to more efficient parameter estimates.

10.1. Joint Copula-Based Stochastic Behavioral Modeling

Keeping in view the methodological concerns outlined in section 3.1., we rewrite the joint probability expression in Eq. (5) in terms of copula representation as (Trivedi and Zimmer 2007):

$$\begin{aligned} P\left(y_{Q_1} = l_1, y_{Q_2} = l_2\right) \\ \left(\omega_{Ql_1}, \omega_{Ql_2}\right) - C_\alpha\left(\omega_{Ql_1}, \omega_{Ql_{2-1}}\right) - C_\alpha\left(\omega_{Ql_1-1}, \omega_{Ql_2}\right) + C_\alpha\left(\omega_{Ql_1-1}, \omega_{Ql_{2-1}}\right) \end{aligned} \tag{6}$$

In Eq. (6), C_α denotes a particular copula (discussed next in detail) that is used to characterize the stochastic dependence between $\aleph_{Q_{l_K}=1}$ and $\aleph_{Q_{l_K}=2}$; and ω is defined as a function of estimable coefficients in β vectors and the thresholds Θ_{l_K} as follows (Yasmin et al. 2014, Wali et al. 2018):

$$\omega_{Ql_1} = F_{\aleph_{Q_{l_K}=1}}\left(\Theta_{l_1} - \beta_1{}'\boldsymbol{x}_{Q_1}\right); \quad \omega_{Ql_1-1} = F_{\aleph_{Q_{l_K}=1}}\left(\Theta_{l_1-1} - \beta_1{}'\boldsymbol{x}_{Q_1}\right) \tag{7}$$

$$\omega_{Ql_2} = F_{\aleph_{Q_{l_K}=2}}\left(\Theta_{l_2} - \beta_2{}'\boldsymbol{x}_{Q_2}\right); \quad \omega_{Ql_2-1} = F_{\aleph_{Q_{l_K}=2}}\left(\Theta_{l_2-1} - \beta_2{}'\boldsymbol{x}_{Q_2}\right) \tag{8}$$

In Eq. (7) and Eq. (8), $F_{\aleph_{Q_{l_K}=1}}$ and $F_{\aleph_{Q_{l_K}=2}}$ represent the cumulative distribution functions of the two marginals ($\aleph_{Q_{l_K}=1}$ and $\aleph_{Q_{l_K}=2}$) for households' participation levels in CS and RH programs. To arrive at the final likelihood function, the individual household-level likelihoods can be summed together as:

$$LL = \prod_{h=1}^{Q} \left\{ \prod_{l_{K=1}, l_{K=2}=1}^{L} \left[P\left(y_{Q_1} = l_1, y_{Q_2} = l_2\right)\right]^{\gamma_{Ql_1}\gamma_{Ql_2}} \right\} \tag{9}$$

The vectors γ_{Ql_1} and γ_{Ql_2} are indicator variables equaling one (1) if household Q exhibits a participation level l_1 in CS and l_2 in RH program, respectively, and zero (0) otherwise.

In this study, C_α in Eq. (6) represents a diverse suite of elliptical and Archimedean copulas capturing complex forms of stochastic dependence contours. For the joint bivariate ordered probit model with dependency in unobservables of the two outcomes, copula approach is used to model the joint distributions in a closed form with direct maximum likelihood procedures. A mathematical construct, copula can be conceptualized as a multivariate device used to generate different forms of (stochastic) dependence between random variables with pre-specified marginals – in our case $\aleph_{Q_{l_K}=1}$ and $\aleph_{Q_{l_K}=2}$ with marginal distributions, $F_{\aleph_{Q_{l_K}=1}}(.)$ and $F_{\aleph_{Q_{l_K}=2}}(.)$, respectively. Introduced by Sklar (1959), the copula approach avoids the key limitations of traditional bivariate ordered probit model – allowing us to examine the dependence structure between household participation levels in carsharing and ridesharing programs independent of the univariate margins underlying the joint distribution. Following Sklar (1959), for a pair of continuous random variables $\aleph_{Q_{l_K}=1}$ and $\aleph_{Q_{l_K}=2}$, the joint cumulative distribution function (CDF) can be formulated as (Sklar 1959):

$$\varpi\left(\aleph_{Q_{l_K}=1}, \aleph_{Q_{l_K}=2}\right) = C_\alpha\{A\left(\aleph_{Q_{l_K}=1}\right), B\left(\aleph_{Q_{l_K}=2}\right)\} \tag{10}$$

Where: $A\left(\aleph_{Q_{l_K}=1}\right)$ and $B\left(\aleph_{Q_{l_K}=2}\right)$ are the marginal distributions of the unobservables associated with the two response outcomes: household participation levels in CS and RH programs. C is the copula device, arranged as C: $[0,1]^2 \rightarrow [0,1]$, used to tie the two marginals $A\left(\aleph_{Q_{l_K}=1}\right)$ and $B\left(\aleph_{Q_{l_K}=2}\right)$ with a dependence parameter α governing the stochastic dependence between $\aleph_{Q_{l_K}=1}$ and $\aleph_{Q_{l_K}=2}$. The stochastic dependence parameter α is only dependent on the copula used and not on the underlying marginals. If the marginal distributions $A\left(\aleph_{Q_{l_K}=1}\right)$ and $B\left(\aleph_{Q_{l_K}=2}\right)$ are assumed to be standard normal (yielding the ordered probit model), the stochastic dependence between $\aleph_{Q_{l_K}=1}$ and $\aleph_{Q_{l_K}=2}$ can then be modeled using a specific copula device. A broad suite of copulas has been used in transportation literature, with elliptical and Archimedean as the two major classes (Bhat and Eluru 2009, Yasmin et al. 2014, Wang et al. 2015, Wali et al. 2018, Shin et al. 2022, Wali and Khattak 2022, Phuksuksakul et al. 2023).

10.2. Elliptical and Archimedean Copulas

Elliptical copulas are directly derived from inverting the Sklar's theorem in Eq. (10). Building on the above exposition, if the two margins, $\aleph_{Q_{l_K}=1}$ and $\aleph_{Q_{l_K}=2}$, are invertible, then the elliptical copula family is derived as (Nelsen 2007):

$$C\left(\aleph_{Q_{l_K}=1}, \aleph_{Q_{l_K}=2}\right) = F\{A^{-1}\left(\aleph_{Q_{l_K}=1}\right), B^{-1}\left(\aleph_{Q_{l_K}=2}\right)\} \tag{11}$$

Among elliptical copulas, Gaussian copula is the most famous comprehensive multivariate distribution with the form (Trivedi and Zimmer 2007):

$$C\left(\aleph_{Q_{l_K}=1}, \aleph_{Q_{l_K}=2}\right) = \Phi_p\{\phi^{-1}\left(\aleph_{Q_{l_K}=1}\right), \phi^{-1}\left(\aleph_{Q_{l_K}=2}\right)\} \tag{12}$$

Where: Φ_p is the bivariate standard normal distribution function with the stochastic dependence characterized by p (α, or referred to as θ alternatively in other studies) (dependence parameter) ranging as $(-1 \leq p \leq 1)$; ϕ^{-1} are the inverted univariate distributions (in our case standard normal) for the two response outcomes. Gaussian copula is termed "comprehensive" in that it can capture positive as well as negative dependence between two stochastic variables – with a symmetric dependence around the center of the bivariate distribution (Trivedi and Zimmer 2007). Shown in Figure A1, Gaussian copula is characterized by the property of asymptotic independence (Bhat and Eluru 2009), i.e., extreme tail events tend to be independent in each margin regardless of the actual correlation between the two margins. The implication of this is that the tail dependence in Gaussian copula approaches zero (0) since the density almost always "thins away" in the tails of the distribution (Figure A1). The asymptotic independence in Gaussian copula also unrealistically implies an equal dependence between household participations levels in CS and RH programs in the upper and lower tails of the joint density. If the marginals are assumed to be normal (which is the case in ordered probit framework), the Gaussian copula reduces to a standard bivariate normal density.

Compared to the Gaussian copula, Archimedean family of copulas is another popular suite that covers a broad range of symmetrical or asymmetrical stochastic dependence structures through convenient closed-form expressions – ultimately relaxing the asymptotic independence assumption rooted in the elliptical Gaussian copula. Starting with Bhat and Eluru (2009), a growing spectrum of studies has harnessed single parameter Archimedean copulas to model joint behavioral processes (Bhat and Eluru 2009, Spissu et al. 2009, Yasmin et al. 2014, Wang et al. 2015, Wali et al. 2018, Wali et al. 2018). The standard Archimedean copulas have been extended to multi-parameter mixtures of Archimedean copulas and its survival variants to model other behavioral processes (Wali et al. 2018). The mathematical formulations, generator functions, and other key characteristics of the elliptical and Archimedean copulas are provided in Table A1. For details, see (Bhat and Eluru 2009, Wali et al. 2018). The copula-based joint likelihood functions are maximized with respect to lambda (λ) as a transformation of the actual dependence parameter (α). The λ to α mapping functions ($\lambda[\alpha]$) used are α (Frank copula), $tanh^{-1}(\alpha)$ (Gaussian), $e^{\alpha} - 1$ (Clayton), and $e^{\alpha} + 1$ (Gumbell and Joe). Only α is needed for model interpretation; however, Table 4 in the manuscript provides both λ and α for completeness.

TABLE A1. Mathematical Expressions and Characteristics of Elliptical and Archimedean Copulas

Copula	Expression/Generator	Limit/range of dependence parameter (α)	α_{IND}	Kendall's τ | α	Range of Kendall's τ	Lower & Upper Tail Dependence
Bivariate Elliptical Copula						
Gaussian	$C\left(\aleph_{Q_{l_K}=1}, \aleph_{Q_{l_K}=2}\right) = \Phi_\alpha\{\phi^{-1}\left(\aleph_{Q_{l_K}=1}\right), \phi^{-1}\left(\aleph_{Q_{l_K}=2}\right)\}$	$-1 \leq \alpha \leq 1$	0	$\frac{2}{\pi} arcsin(\alpha)$	$-1 \leq \tau \leq 1$	(0,0)
Archimedean Copula Families						
Frank	$-ln\left(\frac{\exp(-\alpha t) - 1}{\exp(-\alpha) - 1}\right)$	$\alpha \in [-\infty, \infty)$	0	$1 - \frac{4}{\alpha}\{1 - D_1(\alpha)\}$	$-1 < \tau < 1$	(0,0)
Gumbel (G-H) copula	$(-lnt)^\alpha$	$\alpha \in [1, \infty)$	1	$\frac{\alpha - 1}{\alpha}$	$0 \leq \tau < 1$	$(0, 2 - 2^{\frac{1}{\alpha}})$
Joe	$-\ln[1 - (1 - t)^\alpha]$	$\alpha \in [1, \infty)$	1	$1 + \frac{4}{\alpha} D_2(\alpha)$	$0 \leq \tau < 1$	$(0, 2 - 2^{\frac{1}{\alpha}})$
Clayton	$\frac{1}{\alpha}(t^{-\alpha} - 1)$	$\alpha \in [-1, \infty)$	0	$\frac{\alpha}{\alpha + 2}$	$0 \leq \tau < 1$	$(2^{-\alpha}, 0)$

$D_1(\alpha)$ – Debye Function of the first kind: $D_1(\alpha) = \frac{1}{\alpha}\int_0^\alpha \frac{t}{e^t - 1} dt$

$D_2(\alpha)$ – Debye Function of the second kind: $D_2(\alpha) = \int_{t=0}^1 tlog(t)(1 - t)^{2(1-\alpha)/\alpha} dt$

Notes: α_{IND} indicates the value of dependence parameter (α) associated with stochastic independence. For details, see (Nelsen 2007, Joe 2014).

The Frank copula, from the Archimedean family, is also a "comprehensive" copula in that it can model both positive as well as negative stochastic dependence structures between participation levels in CS and RH programs. Compared to Gaussian copula, the Frank copula differs in that it characterizes a stronger dependence structure in the center and a relatively weaker stochastic dependency in the tails of the multivariate distribution (see Figure A1). Termed as "non-comprehensive" copulas, Clayton, Gumbel, and Joe can typically only characterize positive stochastic dependence structures with varying levels of asymmetry in the tails of the bivariate distribution[9] (Bhat and Eluru 2009). The Clayton copula characterizes stronger dependence in the left tail and relatively weaker stochastic dependence in the right tail of the distribution. In our case, a Clayton copula would imply the presence of stronger dependence between households' lower participation levels in CS and RH programs, and a weaker stochastic dependence between households' higher participation levels in the two programs (Figure A1). On the contrary, Gumbel and Joe copulas are ideally suited for stronger dependence in the right tail and a spread-out/weaker dependence in the left tail of the bivariate distribution (Bhat and Eluru 2009). Compared to Gumbel copula, the right tail dependence is, nonetheless, stronger for Joe copula (Figure A1).

10.3. Finite Mixture Modeling - Heterogeneity in Marginals

While the copula approach laid out above can capture complex forms of stochastic dependence between the two response outcomes, it assumes homogeneity in the two marginals contributing to the joint density (McLachlan et al. 2019). However, the distributions of unobservables (marginals) determining households'

[9] A positive dependence can also be modeled using the non-comprehensive Archimedean copulas by making the error terms associated with the two equations negative or alternatively by 'rotating' the non-comprehensive copulas by 90 or 270 degrees. For details, see section 3.1.4 in (Wali et al. 2018).

participation levels in carsharing and ridesharing programs may exhibit heterogeneity. By using normal mixtures derived from finite mixture modeling techniques (Arcidiacono and Jones 2003, McLachlan et al. 2019), we extend the copula based joint methodological framework to account for heterogeneity in the marginals underlying the joint distribution. Following the earlier exposition, let $\aleph_{Q_{l_K}=1}$ and $\aleph_{Q_{l_K}=2}$ be the unobservables and consider $F_{\aleph_{Q_{l_K}=1}}(.)$ and $F_{\aleph_{Q_{l_K}=2}}(.)$ be the marginal distributions of the two marginals. For each of the marginals/residual terms, $\aleph_{Q_{l_K}=1}$ and $\aleph_{Q_{l_K}=2}$, the marginal distributions, $F_{\aleph_{Q_{l_K}=1}}(.)$ and $F_{\aleph_{Q_{l_K}=2}}(.)$ can be specified as a homogeneous normal component (standard normal in case of ordered probit) or a finite mixture of two normal components[10] (Everitt 2013, McLachlan et al. 2019). Precisely, the following parameterization is used:

$$F_{\aleph_{Q_{l_K}=1}}(\aleph_{Q_{l_K}=1}) = \pi_{\aleph_{Q_{l_K}=1}}\phi\left(\frac{\aleph_{Q_{l_K}=1} - \mu_{1,\aleph_{Q_{l_K}=1}}}{\sigma_{1,\aleph_{Q_{l_K}=1}}}\right) + \left(1 - \pi_{\aleph_{Q_{l_K}=1}}\right)\phi\left(\frac{\aleph_{Q_{l_K}=1} - \mu_{2,\aleph_{Q_{l_K}=1}}}{\sigma_{2,\aleph_{Q_{l_K}=1}}}\right) \tag{13}$$

$$F_{\aleph_{Q_{l_K}=2}}(\aleph_{Q_{l_K}=2}) = \pi_{\aleph_{Q_{l_K}=2}}\phi\left(\frac{\aleph_{Q_{l_K}=2} - \mu_{1,\aleph_{Q_{l_K}=2}}}{\sigma_{1,\aleph_{Q_{l_K}=2}}}\right) + \left(1 - \pi_{\aleph_{Q_{l_K}=2}}\right)\phi\left(\frac{\aleph_{Q_{l_K}=2} - \mu_{2,\aleph_{Q_{l_K}=2}}}{\sigma_{2,\aleph_{Q_{l_K}=2}}}\right)$$

Where: ϕ indicates the normal distribution function; $\pi_{\aleph_{Q_{l_K}=1}}$ and $\pi_{\aleph_{Q_{l_K}=2}}$ are the mixing parameters/probabilities associated with each of the two-part mixture of normals for the marginals in CS and RH equations; $[\mu_{1,\aleph_{Q_{l_K}=1}}, \mu_{2,\aleph_{Q_{l_K}=1}}]$ and $[\sigma_{1,\aleph_{Q_{l_K}=1}}, \sigma_{2,\aleph_{Q_{l_K}=1}}]$ are the estimable location and scale parameters for the two-part mixture of normal for the carsharing equation; and $[\mu_{1,\aleph_{Q_{l_K}=2}}, \mu_{2,\aleph_{Q_{l_K}=2}}]$ and $[\sigma_{1,\aleph_{Q_{l_K}=2}}, \sigma_{2,\aleph_{Q_{l_K}=2}}]$ correspond to the location and scale parameters for the finite mixture associated with marginals of RH equation. Finally, to satisfy mean and variance normalizations, the location and scale parameters are parameterized as follows in a finite mixture modeling setup:

$$\pi_{\aleph_{Q_{l_K}=1}}\mu_{1,\aleph_{Q_{l_K}=1}} + (1 - \pi_{\aleph_{Q_{l_K}=1}})\mu_{2,\aleph_{Q_{l_K}=1}} \equiv 0 \tag{14}$$

[10] We note that the two-component mixture specification is not limiting especially with the use of copulas (that track stochastic dependence) and a broad spectrum of demographic and behavioral covariates in model specification. For the dataset under consideration, we expect that copula models with higher order (> 2 components) mixtures would most likely fail to converge. Additionally, it is highly likely that the structural parameters underlying the higher order (> 2 components) mixtures would be statistically insignificant. This expectation is based on the result that the structural parameters were statistically insignificant even when we specified *different* two-component marginal mixtures for the ride-hailing and carsharing equations in the copula-based joint framework (as discussed in section 4). However, this result concerning the little (if any) usefulness of higher order mixtures may not be transferrable to other datasets though. Thus, future studies may explore the usefulness of higher order mixtures to better track latent heterogeneity in other empirical contexts.

$$\pi_{\aleph_{Q_{l_K}=1}}\left(\sigma^2_{1,\aleph_{Q_{l_K}=1}} + \mu^2_{1,\aleph_{Q_{l_K}=1}}\right) + \left(1 - \pi_{\aleph_{Q_{l_K}=1}}\right)\left(\sigma^2_{2,\aleph_{Q_{l_K}=1}} + \mu^2_{2,\aleph_{Q_{l_K}=1}}\right) = 1$$

And a similar finite mixture parametrization can be used for the location and scale parameters in the marginals of ridesharing equation:

$$\pi_{\aleph_{Q_{l_K}=2}}\mu_{1,\aleph_{Q_{l_K}=2}} + (1 - \pi_{\aleph_{Q_{l_K}=2}})\mu_{2,\aleph_{Q_{l_K}=2}} \equiv 0 \tag{15}$$

$$\pi_{\aleph_{Q_{l_K}=2}}\left(\sigma^2_{1,\aleph_{Q_{l_K}=2}} + \mu^2_{1,\aleph_{Q_{l_K}=2}}\right) + \left(1 - \pi_{\aleph_{Q_{l_K}=2}}\right)\left(\sigma^2_{2,\aleph_{Q_{l_K}=2}} + \mu^2_{2,\aleph_{Q_{l_K}=2}}\right) = 1$$

With the ability to capture different distributional shapes with bimodality and/or skewness, the above finite mixtures can capture the unobserved behavioral heterogeneity in factors determining the households' participation levels in CS and RH programs. Altogether, the copula based joint framework when fused with finite mixtures allows a deeper and more granular understanding of the stochastic dependence between households' participation levels in CS and RH programs - and a fuller picture of the underlying unobserved behavioral heterogeneity in unobserved factors influencing the use of CS and RH programs.

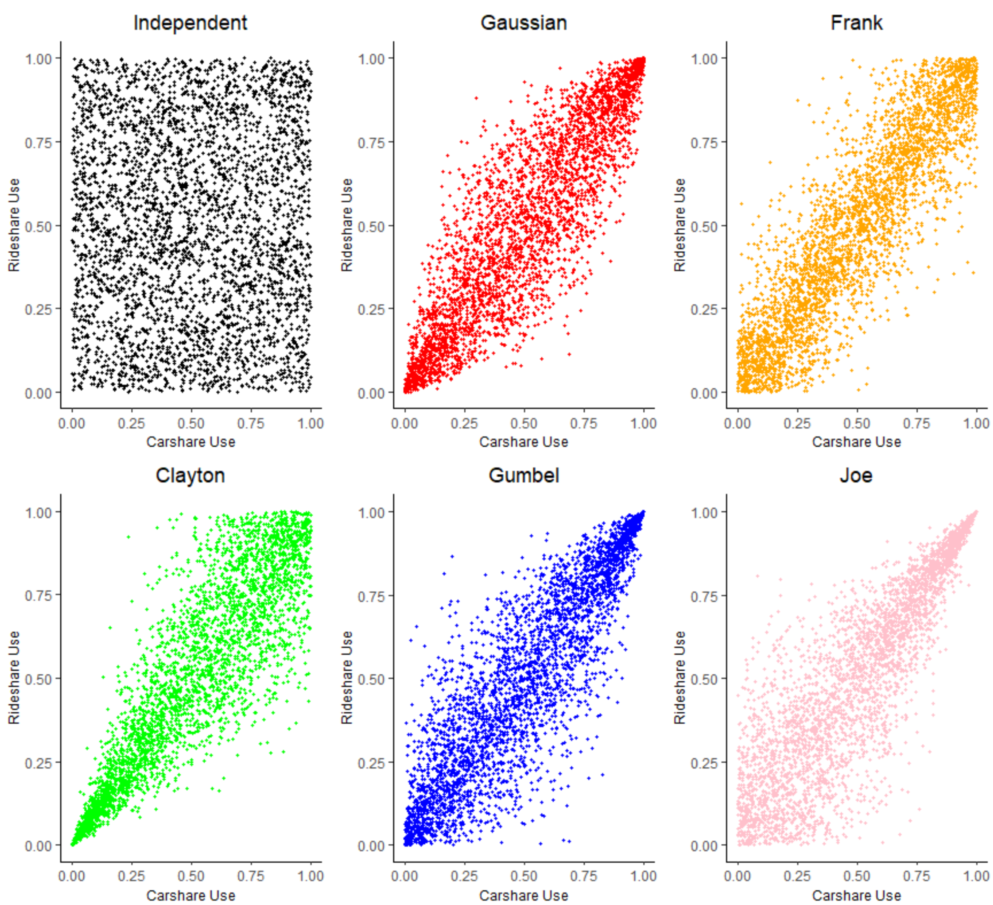

FIGURE A1: Comparison of Elliptical and Archimedean Copulas

Notes: For illustration, 3600 samples simulated from each copula with copula dependence parameters (θ *or* α) corresponding to a Kendall's τ of 0.75 ($-1 \leq \tau \leq 1$).

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