Analyzing Post-COVID Commuting Preferences and Frequencies in California: A Hybrid Multiple Discrete-Continuous Extreme Value Approach

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SHORT SUMMARY (142 WORDS)

Before the COVID-19 pandemic, commuting trips were a significant part of vehicle miles traveled (VMT) in the U.S. Although commuting decreased during the pandemic, California's highway traffic has nearly returned to pre-pandemic levels. This study examines post-pandemic commuting preferences using data from 1,458 California residents. A hybrid multiple discrete-continuous extreme value (HMDCEV) model was developed to simultaneously analyze the impacts of latent attitudes and both direct and indirect effects of observable variables on commuting choices and respective frequencies. Results indicate latent attitudes such as anti-car, car-captive, pro-biking and pro-environment, influence commuting preferences. Additionally, socio-demographics, residential characteristics, and employment characteristics play crucial roles. Driving alone in a private vehicle was found to be the most popular commuting mode, followed by telework, while ride-hailing was the least popular. These findings can help policymakers promote sustainable transportation by addressing both observable factors and underlying attitudes.

Keywords: Commuting, Discrete choice modelling, Mode choice, Trip frequency

1. INTRODUCTION

Prior to the COVID-19 pandemic in 2017, commuting accounted for 28% of the vehicle miles traveled (VMT) in the U.S. with 88% of workers using private vehicles for commuting (McGuckin & Fucci, 2018). By March 2020, commuting dropped 75% due to COVID-19 (Wang et al., 2024). By 2021, total U.S. VMT rebounded, recovering 64% of its 2020 drop (United States Department of Transportation. Bureau of Transportation Statistics, 2023). However, increased teleworking kept 2022 commute-related trips 28% below 2017 levels (Bricka et al., 2022). Despite fewer trips, commuting VMT still made up 30% of total VMT, with 91% of workers relying on private vehicles.

Post-pandemic, more workers plan to telework, but infrequent teleworking can increase VMT compared to regular commuting (Wang et al., 2024). Thus, as pandemic effects fade, congestion and commuting-related VMT are nearing pre-pandemic. Most commuting trips rely on private vehicles, causing congestion, air and noise pollution, and emissions (Cervero & Gorham, 1995; Mitra & Saphores, 2019). Therefore, understanding commuter behavior, mode choices, and their frequencies is vital in addressing evolving work, technological, societal, and environmental priorities.

Numerous studies have identified the determinants of commuting mode choices among U.S. workers. Demographic factors such as age and residential location significantly influence commuting behavior in California (Beckman & Goulias, 2008). Residential and neighborhood characteristics play a critical role, particularly in areas with strong public transit access, which see higher rates of transit and active mobility (Cervero & Duncan, 2002; Cervero & Gorham, 1995). However, another study found that when accounting for attitudinal, lifestyle, and sociodemographic variables, neighborhood type has less influence on travel behavior, underscoring the importance of addressing self-selection effects (Bagley & Mokhtarian, 2002).

Attitudes, perceptions, and satisfaction with transportation modes also significantly shape commuting decisions (Donald et al., 2014). Factors such as subjective norms and perceived behavioral control indirectly affect mode choices by shaping intention and habit. The built environment, safety concerns, travel time valuation, and household responsibilities, including childcare, also play roles in active transportation decisions (Cusack, 2021).

The pandemic reshaped commuting, with infection fears driving a shift from public transit to private vehicles, reduced transit services, and increased teleworking (Khatun & Saphores, 2023; Parker et al., 2021). Lower-income transit riders experienced smaller reductions in trips and travel distances than higher-income riders, reflecting limited flexibility in travel adjustments (Parker et al., 2021). Encouragingly, some commuters grew more inclined toward walking and biking during the pandemic. (Khatun & Saphores, 2023).

Recent evidence indicates that commuting-related VMT is rapidly returning to pre-pandemic levels (United States Department of Transportation. Bureau of Transportation Statistics, 2023). This resurgence, coupled with the pressing need to better understand commuting behaviors in California, underscores the importance of this study. This research investigates factors influencing commuting mode choices and their corresponding usage frequencies among California workers, integrating both traditional factors and users' attitudes and perceptions. To achieve these objectives, the research employs a hybrid multiple discrete-continuous extreme value (HMDCEV) model using data collected in California.

2. METHODOLOGY

This study's dataset was from the Fall 2023 wave of the California Mobility Panel, a longitudinal project examining emerging transportation technologies and mobility trends on travel behavior and vehicle ownership in California. Administered by the 3 Revolutions Future Mobility (3RFM) Program at the Institute of Transportation Studies, UC Davis, the Fall 2023 wave gathered data from 6,462 respondents using a multi-channel sampling strategy. While this approach enhances societal coverage, the resulting sample is considered closer to a convenience sample rather than representative. For these data, analysis relies on development of models that establish the effect of various factors on behavioral outcomes.

Rigorous data cleaning ensured the dataset's quality and relevance. Of the initial 6,469 respondents, only those with verified California zip codes were retained. Further criteria required participants to be full-time workers employed during July–August 2023 and at least some commuting to a non-home work-location. Respondents who were also students or had missing data on key variables were excluded. These steps yielded a final sample of 1,458 respondents, ensuring alignment with the study's objectives and maintaining data quality.

The survey included seven sections on socio-demographics, attitudes, employment, household characteristics, travel behavior, shopping patterns, and vehicle ownership, enabling analysis of commuting decisions and mobility trends in California.

Hybrid multiple discrete-continuous extreme value (HMDCEV) model

The structure of the HMDCEV model used in this study is depicted in Figure 1. The dependent variable is the multiple-discrete continuous (MDC) choice of allocating a pre-determined number of 'commute trips' to an available set of mode options, as described in the introduction. A key feature is that the choice to work from home ('telework') is treated as another mode choice option (even though work occurs at home). The 'kernel' of the model is the multiple discrete-continuous extreme value (MDCEV) model proposed by Bhat (Bhat, 2005). In Figure 1, the MDC components of the model (inside the green box) are the utility (a single latent variable), the explanatory variables on the left, and the dependent variables at the bottom. The allocation decision is assumed to be based on maximizing the (direct) utility subject to the commute trip constraint.

The model is extended to a 'hybrid model' by integrating a structural/measurement equation model consisting of components (inside the red box in Fig.1.) that include latent variables (representing unobservable attitudes that directly influence utility), and indicator variables (that provide observed information on attitudes that help identify the effects), where the arrows from the latent variables to the indicators represent measurement equations. The source of the indicators is the respondent' level of agreement with the statements on the right, measured using a five-point Likert scale. Finally, arrows from the explanatory variables to the latent variables represent structural equations. The integrated model is implemented in the Apollo R package (Hess & Palma, 2019), which performs (full information) maximum simulated likelihood estimation using the BGW R package (Bunch et al., 1993).

3. RESULTS AND DISCUSSION

This section presents the estimation results for the HMDCEV model depicted in Fig. 1.

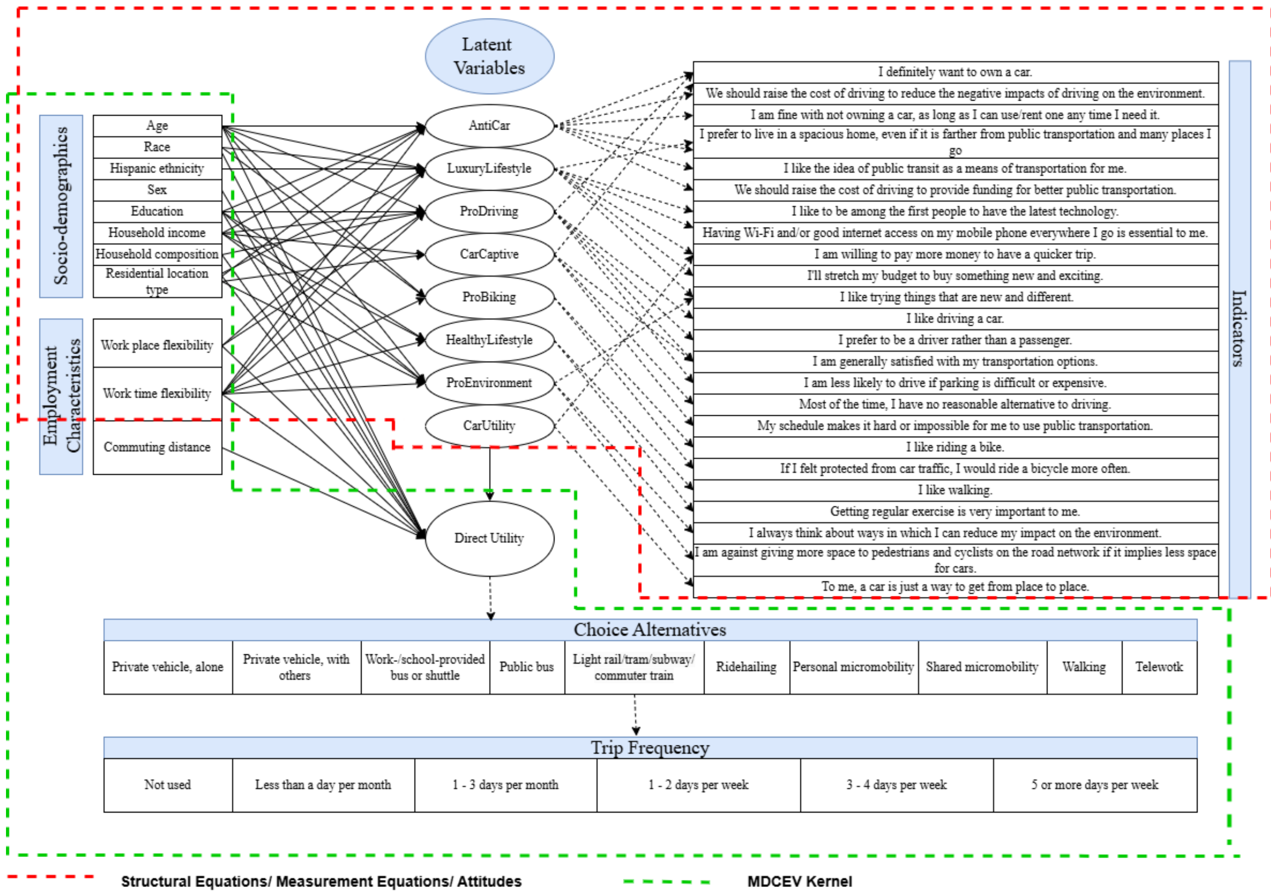

Figure 1: HMDCEV Model
[MDCEV kernel in green box, structural/measurement equations in red box]

Preliminary estimates of MDCEV models were performed to provide a starting point. Exploratory factor analysis (EFA) was separately performed on the indicator variables to provide guidance on the number of latent variables to include, their interpretation, and the measurement equation structure. Preliminary steps also included producing factor scores and incorporating them in MDCEV models for testing purposes, as well as exploratory regressions to test structural equation specifications. The result was our adoption of the eight latent variables with the names shown in Figure 1. To conserve space, in the sequel we omit results from measurement equation coefficients and focus on coefficients for the choice model and the structural equations.

Multiple Discrete Continuous Extreme Value (MDCEV) Choice Model

Tables 2 and 3 provide coefficient estimates for the MDCEV model, highlighting the direct effects of observed exogenous variables as well as latent factors representing (unobservable) attitudes. The base choice alternative is private vehicle driving alone. For latent variables, a base value of zero corresponds to the median of the attitude distributions for the respondents. The other explanatory variables are almost exclusively implemented using dummy variable coding, so that, e.g., a "base" respondent is: ≥ 65 years of age, male, no bachelor's degree, non-Hispanic and non-Asian, with income from \$75 to \$150K, living in a rural area, with some flexibility in their choice of working location and work time, not living alone, with no children/grandchildren in the home, and either zero or 1 worker. There are also two continuous interaction variables involving commute distance. So, for a “base respondent” thus described, with “average” attitudes and a very small commute distance, the estimated constants represent the baseline utilities for the competing choice options. As already noted, private vehicle driving alone has a base coefficient of zero: all other constants are negative, indicating that private vehicle driving alone has the largest baseline utility, with Private vehicle (with others) and Telework ranking second and third. The remaining modes have negative constants with notably larger magnitudes, which is consistent with their observed smaller conditional choice shares and usage frequencies.

In addition to baseline constants, each choice alternative has associated with it a gamma parameter. While a full discussion is beyond the scope of this short paper, these parameters capture a satiation effect for utility, so that the marginal utility of each alternative decreases as a function of usage frequency. It is this effect that allows for a respondent to choose more than one discrete alternative in the MDCEV modeling framework—see, e.g., Bhat (2008). In our results the gamma coefficients have similar values, indicating a similar satiation effect across all alternatives.

For these direct effects, many of the latent attitude factors are statistically significant and provide meaningful insights. It is important to note that the latent variables are continuous values that lie along a “dimension” with both positive and negative values, so that the interpretation goes in both directions, getting stronger with increasing magnitudes. Individuals with larger anti-car attitudes are more likely to use work-provided shuttles, light rail, personal micromobility, walking, or telework, and less likely to carpool. Individuals with increasing Car-captive perceptions avoid shuttles, public transit, micromobility, walking, and telework. Individuals with higher Luxury orientation have increased preference for public buses, ridehailing, and shared micromobility, and lower preference for Telework. Individuals with a higher Pro-driving attitude show some increased preference for ridehailing (and perhaps shared micromobility) versus all other modes, while an increase in Car-utility perception negatively affects the baseline utility for public transit, micromobility, and walking. An increasing Pro-biking attitude positively influences baseline utility for micromobility and walking, aligning with prior research.

The following paragraphs highlight the direct influence of observed variables, including socio-demographics, on commuting mode choices.

Table 2 shows that respondents aged 35–64 are less likely to choose private vehicles with others for commuting. Female respondents are more inclined to telework than males, while Hispanic individuals favor private vehicles with others and ridehailing. Asian respondents also prefer private vehicles with others, consistent with previous literature on post-COVID-19 mode choice decisions (Brown et al., 2022; Brown & Williams, 2023). Urban residents are more likely to use work-provided shuttles, public buses, light rail, and shared micromobility, while those in suburban or small-town areas prefer teleworking, aligning with prior studies on residential location and commuting mode choice (Cervero & Duncan, 2002; Cervero & Gorham, 1995).

Employment flexibility plays a significant role in mode choice. Absolute workplace flexibility increases the likelihood of using ridehailing, micromobility, walking, or teleworking, whereas absolute flexibility in working hours reduces the likelihood of teleworking.

Household characteristics are also crucial. Single-person households are more likely to choose walking, while individuals with children or grandchildren are more likely to use private vehicles with others, less likely to telework, and more inclined toward shared micromobility. Households with two or more employed individuals show a preference for private vehicles with others.

It was found that in urban areas, longer commutes encourage personal micromobility use, while in rural settings, longer distances increase the likelihood of teleworking.

Table 1: Estimation results from the Structural Equation

Socio-demographic variables	**Category**	**Latent factors**						
		Anti-car	Luxury-lifestyle	Pro-driving	Car-captive	Pro-biking	Healthy-lifestyle	Pro-environment
Age (years) (base: 65 and above)	18-34	0.07 (0.69)	-0.07 (-0.78)	-0.21 (-2.77)		0.35 (4.63)		0.21 (0.34)
	35-64	-0.40 (-5.12)	-0.34 (-4.35)			-0.12 (-2.19)		-1.29 (-0.73)
Ethnicity (base: Non-Hispanic)	Hispanic		0.16 (1.90)					
Race								
(base: Non-Black)	Black		0.23 (1.21)					
(base: Non-Mixed)	Mixed					0.52 (3.06)		
Bachelor's degree (base: No)	Yes	0.18 (2.32)		-0.26 (-3.97)			0.37 (2.25)	0.86 (0.64)
Annual household income (USD) (base: Middle (75,000-149,999))	Low (< 74,999)				-0.11 (-1.22)		-0.53 (-2.53)	
	High (> 150,000)	0.30 (3.42)		-0.23 (-2.64)			0.36 (1.78)	0.97 (0.83)
Neighborhood type	Urban	0.45 (6.46)			-0.42 (-4.65)			1.70 (0.82)
	Small town		-0.41 (-3.12)					
Flexibility in workplace location (base: Some flexibility)	No Flexibility	-0.37 (-5.10)		-0.24 (-1.76)				
Flexibility in work time (base: Some flexibility)	Absolute flexibility		0.40 (3.64)	0.45 (4.45)		-0.22 (-1.79)		
	No Flexibility						-0.58 (-2.52)	-2.20 (-0.84)
Household members								
(base: No-Children or grandchildren)	Children or grandchildren		0.31 (3.61)	0.47 (6.67)				
(base: No-Spouse)	Spouse		0.08 (0.87)					

Table 2: Estimation results for multiple discrete-continuous extreme value (MDCEV) model Part 1

Variables	Categories	Private vehicle, driving alone	Private vehicle with others	Work-provided bus or shuttle	Public bus	Light rail	Ridehailing	Personal micromobility	Shared micromobility	Walking	Telework
Alternative specific constants											
		0 (NA)	-1.14 (-7.87)	-2.98 (-14.68)	-4.08 (-19.54)	-3.65 (-18.19)	-3.03 (-19.41)	-3.09 (-20.82)	-4.84 (-16.14)	-2.65 (-19.52)	-1.4 (-4.18)
Latent Factors											
Anti-car			-0.08 (-1.57)	0.18 (1.90)		0.55 (6.50)	0.11 (1.57)	0.2 (2.53)		0.14 (1.87)	0.21 (3.44)
Luxury-lifestyle			0.09 (1.59)		0.27 (2.30)		0.36 (4.75)		0.28 (2.26)		-0.14 (-1.79)
Pro-driving			0.06 (1.03)			-0.11 (-1.33)	0.14 (2.1)	0.11 (1.44)	0.23 (1.74)		
Car-captive			-0.09 (-2.88)	-0.95 (-5.03)	-1.55 (-7.23)	-1.28 (-5.55)	-0.87 (-6.83)	-0.84 (-6.5)		-0.7 (-5.58)	-0.24 (-2.29)
Pro-biking					0.08 (0.64)	0.16 (1.2)		0.57 (4.57)	0.56 (3.33)	0.33 (3.27)	
HealthyLifestyle			-0.04 (-0.62)			0.03 (0.44)					
Pro-environment					0.07 (1.32)		0.13 (0.96)				0.23 (1.51)
Car-utility			-0.19 (-3.08)	-1.09 (-6.08)	-1.37 (-6.75)	-1.33 (-6.99)	-1.02 (-7.16)	-1.08 (-5.93)	-1.58 (-7.25)	-0.82 (-5.53)	
Socio-demographics											
Age (years) (base: 65 and above)	35 - 64		-0.18 (-1.97)								0.33 (1.09)
Gender (base: Male)	Female										0.2 (2.42)
Bachelor's degree (Base: No)	Yes										0.06 (0.16)
Ethnicity (base: Non-Hispanic)	Hispanic		0.21 (2.13)				0.44 (3.93)				
Race											
(base: Non-Asian)	Asian		0.29 (2.65)								0.1 (0.79)
Annual household income (USD) (base:Middle (75,000-149,999))	Low (< 74,999)										-0.25 (-1.55)
	High (> 150,000)										0.11 (0.53)

Table 3: Estimation results for multiple discrete-continuous extreme value (MDCEV) model Part 2

Variables	**Categories**	Private vehicle, driving alone	Private vehicle with others	Work-provided bus or shuttle	Public bus	Light rail	Ridehailing	Personal micromobility	Shared micromobility	Walking	Telework
Residential characteristics											
Neighborhood type (base: Rural)	Urban			0.52 (2.47)	0.58 (2.60)	0.3 (1.59)			1.09 (4.49)		
	Suburban										0.73 (2.70)
	Small town					0.05 (0.06)	-0.36 (-1.28)				0.68 (2.04)
Employment Characteristics											
Flexibility in workplace location (base: Some flexibility)	Absolute flexibility						0.43 (2.91)	0.39 (2.58)	0.63 (2.94)	0.49 (3.3)	1.15 (8.93)
Flexibility in work time (base: Some flexibility)	Absolute flexibility				0.15 (0.72)	0.23 (1.21)	-0.04 (-0.23)				-0.61 (-3.82)
Household Characteristics											
Household members											
(base: No_Alone)	Alone									0.37 (2.39)	
(base: No- Children or grandchildren)	Children or grandchildren		0.26 (2.78)				0.12 (1.04)		0.45 (2.03)		-0.29 (-2.63)
(base: No_2 or more employed members)	2 or more employed members		0.2 (2.30)								
Interaction Variables											
Commute distance * Urban								2.681E-08 (2.97)			
Commute distance * Rural											0.01 (4.93)
Satiation parameter (gamma)		0.51 (8.65)	0.38 (13.38)	0.41 (7.32)	0.36 (10.97)	0.29 (10.90)	0.23 (20.1)	0.35 (12.22)	0.27 (9.25)	0.34 (13.91)	0.41 (9.86)
Number of observations		1458									
LL (start)		-55901.5									
LL (final, whole model)		-55881.42									
AIC		112140.8									
BIC		113139.7									

These findings underline the complex interplay of socio-demographics, household characteristics, and latent factors in shaping commuting behavior.

Structural Equation Model of Latent Variables

The prior section focused on direct effects in the MDCEV model and their interpretations. Another key feature of the HMDCEV model is that it includes structural equations to capture the effect of socio-economics and other factors on latent attitudes. Table 1 presents the estimated coefficients for the structural equations, confirming that exogenous socio-demographic attributes significantly influence individual perceptions and attitudes. It is therefore important to note that these factors can have an *indirect* effect on choice and usage by acting *through* the latent factors, even if there are no *direct* effects. For example, we found essentially no direct effect of education level on choice and usage. However, education levels do influence attitudes that in turn affect choice and usage.

The findings show individuals with a bachelor's degree, high income, and urban residence are more anti-car, while those aged 35–64 and with inflexible work hours are less so. Young adults with high income and education are less pro-driving, while flexible workers and those with children/grandchildren are more pro-driving. Urban residents are less car-captive. Pro-biking attitudes are higher among young adults and mixed-race individuals but lower for those aged 35–64. Anti-car attitudes align with a healthy lifestyle, common among high-income, educated individuals. These links between socio-demographics and attitudes offer actionable insights for targeted policy design.

4. CONCLUSIONS

This study examines how socio-demographics, neighborhood, employment characteristics, and latent attitudes influence commuting mode choice and frequency in a post-COVID-19 context. Using the HMDCEV model with ICLV implementation and data from the Fall 2023 California Mobility Panel, the research provides insights into how both observed and latent factors shape commuting behaviors. The study offers key contributions, including extending the MDCEV framework to include latent factors, incorporating telework as a virtual commuting mode, and analyzing individual-level choice sets based on available modes rather than assuming universal availability.

The model results reveal several important patterns. Individuals with a bachelor's degree, high income, and those living in urban areas are more likely to adopt anti-car attitudes, consistent with post-COVID-19 urban travel behavior studies. Those with anti-car attitudes are more likely to prefer work-provided buses or shuttles, light rail, personal micromobility, walking, or teleworking, reflecting a preference for non-car commuting due to environmental and health considerations, as well as better access to public transit. Additionally, Hispanic individuals, those with flexible work hours, and those living with children or grandchildren are more likely to adopt a luxury-lifestyle, favoring modes like public buses, ride-hailing, and shared micromobility. Flexible work hours also correlate with pro-driving attitudes, increasing the use of ride-hailing and shared micromobility, consistent with Sikder's findings that flexible schedules promote ride-hailing adoption.

Urban residents are less likely to be car-captive and are more likely to use public transit, micromobility, and telework. In contrast, car-captive individuals tend to avoid these modes and are less likely to telework. People aged 18–34 show a stronger preference for biking, with pro-biking attitudes correlating with greater use of personal and shared micromobility and walking, in line with existing literature on active commuting preferences among younger individuals. On the other hand, individuals aged 35–64 are less likely to adopt pro-biking attitudes. Anti-car attitudes align with a healthy-lifestyle orientation, which is more prevalent among high-income, educated individuals, while those with low income and inflexible work hours tend to have less healthy-lifestyle attitudes.
The study also finds that the car-utility factor negatively influences the use of work-provided buses, public transit, ride-hailing, micromobility, and walking for commuting. Interaction effects further reveal that, in urban areas, longer commute distances are positively associated with the use of personal micromobility, while in rural areas, longer distances increase the likelihood of teleworking.

These findings underscore the role of socio-demographic characteristics in shaping commuting behaviors and provide actionable insights for policies aimed at promoting sustainable travel modes.

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