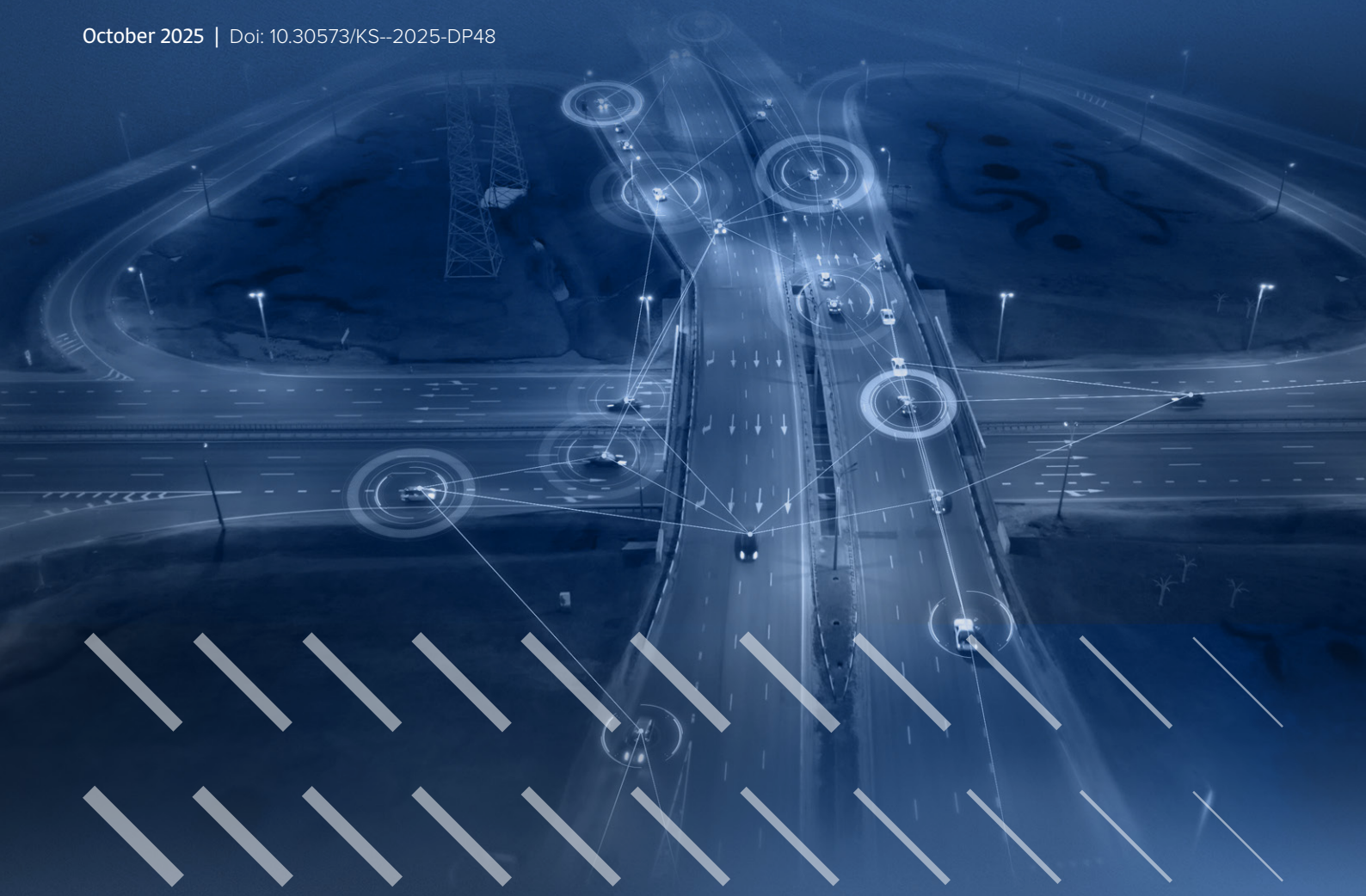
Discussion Paper

Driving the Future

How Connected Autonomous Vehicles Reshape Travel and Energy Demand in Urban and Rural Areas – An Empirical Modeling Approach

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Abstract

The rapid advancement of connected autonomous vehicles (CAVs) is reshaping transportation by significantly impacting travel behavior, fuel efficiency, and mobility patterns in both urban and rural settings. This study develops a nonlinear regression framework to analyze how improvements in fuel efficiency and reductions in time costs – two key features of CAVs – affect vehicle miles traveled (VMT), thereby contributing to the energy rebound effect. While prior research has provided a national-level analysis of these factors, this study extends the scope by differentiating between urban and rural areas and incorporating nonlinear relationships to capture behavioral heterogeneity. Using the 2022 National Household Travel Survey in the United States, this study estimates the elasticity of VMT concerning changes in fuel and time costs.

The findings highlight substantial quantitative impacts within the broader context of CAV adoption. Specifically, the elasticity of travel time cost is estimated at -0.565, while fuel cost elasticity is -0.337. Across all CAV scenarios, the study identifies a consistent and positive rebound effect: improvements in fuel efficiency (ranging from 0% to 40%) and reductions in time costs (up to 45%) result in increased VMT, potentially offsetting anticipated energy savings. This effect is notably more pronounced in rural areas, where longer travel distances and greater reliance on private vehicles amplify the response.

The rebound effect also varies significantly by income level, with time cost elasticity values ranging from -0.51 to -1.84. Higher-income households exhibit the strongest rebound effects, reflecting their greater sensitivity to time cost reductions. These findings underscore a critical challenge for energy efficiency and emissions reduction policies: increased vehicle miles traveled (VMT) resulting from the rebound effect varies significantly by income level, with time cost elasticity estimates ranging from -0.51 to -1.84. Higher-income households exhibit the strongest rebound effects, reflecting their greater sensitivity to time cost reductions. This pattern may substantially diminish the anticipated benefits of such policies, particularly in rural contexts. The study also highlights differences in travel behavior across income groups, showing that higher-income households are more responsive to time cost savings.

This research refines the understanding of CAV-induced energy rebound effects and provides actionable insights for policymakers and urban planners seeking to balance CAV adoption with sustainable mobility goals.

Keywords: Connected Autonomous Vehicles (CAVs), Fuel Cost Elasticity VMT, Energy Rebound, Income Level Travel Behavior, Time Cost Elasticity VMT, Rural Travel Demand, Urban Travel Demand

Introduction

01



Introduction

The rapid evolution of connected autonomous vehicles (CAVs) is ushering in a transformative era in transportation, with profound implications for travel behavior, fuel efficiency, and mobility dynamics in both urban and rural areas. These advancements promise unparalleled convenience, safety, and accessibility. However, they also present complex challenges that warrant careful examination, particularly regarding their long-term impact on energy consumption, environmental sustainability, and societal mobility patterns.

Central to understanding these impacts is the interplay between VMT, fuel efficiency, and time costs. These factors are key drivers of the energy rebound effect, where improvements in fuel efficiency and reductions in travel time costs may induce additional travel, potentially offsetting anticipated energy savings. While the pioneering work of Taiebat, Stolper, and Xu (2018) provided a robust framework for estimating travel demand elasticity and forecasting induced travel behavior, their analysis focused primarily on aggregate national trends. It did not sufficiently differentiate between urban and rural contexts or explore the potential nonlinear relationships in travel demand elasticities.

Building on this foundational research, our study extends the analysis in two critical directions. First, we explicitly disaggregate the energy rebound effects between urban and rural settings, recognizing the distinct differences in travel behavior, infrastructure availability, and accessibility across these regions. By addressing these spatial distinctions, we aim to offer a more nuanced understanding of how CAV adoption impacts energy consumption, providing targeted insights for policymakers and urban planners. Second, we address the limitations of linear assumptions in elasticity modeling by employing a variety of nonlinear modeling techniques to verify the relationships between travel demand and its determinants. This approach allows us to assess the heterogeneity in behavioral responses to changes in travel costs, particularly across diverse socio-economic and demographic groups.

To achieve these objectives, our study leverages the most recent and comprehensive data available – the National Household Travel Survey (NHTS) 2022 (Federal Highway Administration 2022). This updated dataset reflects the latest trends in travel behavior, technological adoption, and energy use, allowing us to produce forecasts that are more representative of the current transportation landscape. Through these contributions, our work provides a more refined and spatially sensitive simulation of CAV-induced energy rebound effects, enhancing our understanding of sustainable mobility pathways and offering actionable insights to mitigate the challenges posed by this transformative technology.

While this study relies on U.S.-based data, its relevance to the Saudi Arabian context is supported by empirical evidence demonstrating structural and behavioral similarities in mobility patterns and vehicle usage characteristics between the two countries.

First, both the U.S. and Saudi Arabia exhibit high car dependency, low public transit ridership, and dispersed urban development, particularly outside major city centers. These commonalities underpin comparable household travel behaviors and vehicle usage patterns (Aljoufie et al. 2013; Litman 2025b).

Second, the U.S. vehicle market has historically served as a benchmark for Saudi Arabia's fleet policy development. Notably, Saudi Arabia adopted the U.S. 2012 Corporate Average Fuel Economy (CAFE) standards in 2016, reflecting a four-year lag in regulatory alignment (Sheldon and Dua 2018). This decision was influenced by the fact that, by 2016, the composition and technical profile of Saudi Arabia's vehicle fleet closely mirrored that of the U.S. market as it stood in 2012.

Such alignment underscores the structural similarities between the two markets and strengthens the rationale for leveraging U.S. data and behavioral trends as a forward-looking proxy to guide transport and energy policy development in Saudi Arabia.

The paper is structured as follows: Section 2 presents a comprehensive review of the existing literature on VMT dynamics, CAV implications, and associated energy and travel rebounds. It identifies key drivers of VMT, including fuel and time costs, and examines how CAVs may alter these relationships. Section 3 outlines the methodology employed in this study, detailing the data sources, econometric models, and analytical techniques used to estimate the impact of CAVs on VMT across different income groups and geographical contexts. Section 4 provides a detailed discussion of the empirical results, comparing the rebound effects of fuel economy and travel time cost reductions in urban and rural areas. Finally, Section 5 concludes with policy implications, highlighting the challenges and opportunities of CAV adoption in managing travel demand and promoting sustainable mobility.

By examining these dynamics, this paper contributes to a deeper understanding of the opportunities and challenges posed by CAVs. While the study draws on findings from the United States, its insights are broadly applicable to other regions, including Saudi Arabia, with a focus on tailoring energy and transportation policies to the unique characteristics of urban and rural areas.

Literature Review

02



Literature Review

The literature review comprises three subsections: (i) determinants of vehicle miles traveled, which examines key drivers of VMT, such as travel time, fuel costs, and socioeconomic factors; (ii) influence of connected autonomous vehicles on VMT determinants, focusing on how CAVs reshape VMT patterns and mobility; and (iii) energy and environmental rebound effects of CAV-induced travel demand, which explores their energy efficiency, eco-routing, and the potential rebounds from increased travel demand.

2.1 Determinants of Vehicle Miles Traveled

VMT is a fundamental metric in transportation studies, reflecting the total distance covered by vehicles within a given timeframe. Understanding the factors that influence VMT offers valuable insights into travel behavior, energy consumption, and broader economic and environmental impacts. This review examines key drivers of VMT, including travel time costs, fuel prices, urban-rural differences, and income levels. It also explores the transformative potential of CAVs in redefining VMT patterns, enhancing fuel efficiency, reducing time costs, and reshaping mobility.

The complex interplay between fuel costs, travel time, and VMT is a central focus for researchers, policymakers, and urban planners. Globally, city planners strive to reduce VMT without disrupting business activities or household mobility. Achieving this balance requires a comprehensive understanding of the factors influencing VMT, along with the development of effective transportation infrastructure and policy strategies.

VMT is influenced by a range of interrelated factors, with travel time emerging as a key determinant.

Research indicates that reductions in travel time, enabled by infrastructure improvements or technological advancements often lead to increased VMT. This phenomenon, known as induced demand, occurs as enhanced accessibility encourages more travel (Cervero 2002; Duranton and Turner 2011). Additionally, changes in travel time affect the elasticity of travel demand, with short-term impacts differing from long-term trends. Reduced time costs can also prompt shifts from public transportation to personal vehicle use, further increasing VMT (Litman 2025a).

These dynamics have important implications: while CAVs may offer individual benefits such as improved convenience and productivity, they risk triggering systemic increases in energy use, emissions, and congestion – potentially offsetting many of the environmental gains associated with their adoption.

Fuel prices play an equally significant role in shaping VMT by directly influencing travel costs. When fuel prices rise, VMT generally decreases, with greater elasticity observed in the short term as individuals quickly adjust their travel behavior (Hughes, Knittel, and Sperling 2008). Over time, policy interventions such as fuel taxes and subsidies for alternative energy vehicles can further influence VMT by encouraging shifts toward sustainable travel practices (Sterner 2007). Prolonged periods of high fuel prices also drive behavioral adaptations, including increased carpooling, fewer discretionary trips, and greater adoption of fuel-efficient vehicles (Cao, Wongmonta, and Choo 2013).

The dynamics of VMT differ significantly between urban and rural areas due to variations in population density, infrastructure, and accessibility. Metropolitan areas, characterized by shorter trip lengths and higher densities, typically show lower VMT per capita compared to rural regions (Ngo et al. 2024). In contrast, rural areas often lack robust public transportation systems, resulting in greater reliance on personal vehicles. Additionally, socioeconomic factors such as income levels and employment opportunities influence travel behavior, with rural populations generally displaying distinct VMT patterns compared to their urban counterparts (Aderibigbe and Gumbo 2022).

Income levels also play a role in travel behavior and VMT. Higher incomes facilitate greater vehicle ownership and support discretionary travel, resulting in increased VMT (Federal Highway Administration 2018). In contrast, economic downturns or recessions reduce disposable incomes, often resulting in decreased travel activity. For instance, during the 2007-2009 recession in the United States, there was a notable decline in auto output's share of gross domestic product (GDP), reflecting reduced travel activity amid economic hardships (Samaddar and Bachman 2022). These shifts underscore the sensitivity of VMT to economic conditions and the affordability of travel.

As these traditional factors continue to influence VMT dynamics, emerging technologies are poised to redefine the transportation landscape. Among these, CAV technology stands out as a transformative force, ushering in a new era of mobility. By integrating advanced communication systems and autonomous capabilities, CAVs promise to enhance mobility, safety, and convenience. However, they also introduce uncertainties, particularly regarding their potential impacts on energy demand, travel patterns, and environmental outcomes.

2.2 Influence of Connected Autonomous Vehicles on VMT Determinants

The implications of CAV adoption on VMT, travel behavior, and urban planning warrant closer examination as we consider the future of transportation systems. CAVs are expected to significantly influence VMT trends due to their convenience, accessibility, and operational flexibility. One of the primary drivers of increased VMT is the reduction in travel effort and time costs. With CAVs taking over the driving task, passengers can travel more comfortably, which may lead to an increase in discretionary travel (Milakis et al. 2017). Additionally, CAVs provide mobility opportunities for previously underserved populations, including the elderly and disabled, further contributing to higher VMT (Martínez-Buelvas et al. 2022).

Another critical factor is the emergence of empty vehicle travel. Unlike traditional vehicles, CAVs may undertake trips without passengers, such as returning home after dropping someone off or repositioning themselves to a different location. This phenomenon poses unique challenges to VMT management, as these empty trips add to overall road usage and congestion (Zhang and Guhathakurta 2017). To mitigate these effects, policymakers should consider implementing strategies such as dynamic pricing or operational restrictions on empty (unoccupied) vehicle movements (Fagnant and Kockelman 2015).

CAVs hold the promise of improving fuel efficiency through optimized driving patterns. By leveraging advanced algorithms and communication technologies, these vehicles can achieve smoother acceleration and deceleration, reduce idling times, and select energy-efficient routes (Taiebat, Stolper, and Xu 2018). Such improvements could contribute to substantial energy savings and reduced emissions. However, these benefits must be weighed against potential energy trade-offs. The anticipated rise in VMT due to CAV adoption could offset gains in fuel efficiency, leading to increased overall energy consumption. This necessitates the implementation of robust energy policies, such as integrating renewable energy sources for electric CAVs or encouraging energy-efficient vehicle designs (Taiebat et al. 2019). Balancing these trade-offs will be essential to ensuring that the environmental benefits of CAVs are fully realized.

Beyond energy considerations, the shift in driving responsibilities from individuals to CAV systems is likely to transform travel behavior and perceptions of time costs. Freed from the need to actively drive, passengers can repurpose travel time for work, leisure, or other productive activities. This reduction in the perceived cost of travel could make longer trips more acceptable and desirable to travelers (Cohen and Hopkins 2018; Yueshuai He, Jiang, and Ma 2022).

This behavioral shift, along with the expansion of Transportation Network Companies (TNCs), such as Uber and Lyft, is expected to impact VMT with the anticipated adoption of autonomous vehicles (Martin, Shaheen, and Wolfe 2024; Choi, Guhathakurta, and Pande 2022). By offering convenient, affordable, and accessible travel options, TNCs reduce the effort and cost associated with transportation, making travel more appealing and less burdensome. This increased convenience could lower the perceived value of travel time, potentially leading to a rise in VMT (Clewlow and Mishra 2017). As CAVs become more integrated into transportation systems in the coming decades, they are expected to play a pivotal yet disruptive role in reshaping transportation markets and influencing traveler behavior (Cohen and Hopkins 2018; Garikapati and Shetiya 2024).

2.3 Energy and Environmental Rebound Effects of CAV-Induced Travel Demand

One approach to evaluating the travel and energy implications of CAVs is to analyze the demand response to changes in energy efficiency and travel costs introduced by CAV technologies. The energy and travel implications of CAVs are primarily influenced by two key factors, as highlighted in the literature: travel demand elasticities (such as travel costs, income levels, and travel mode) and variations in cost structures (including travel time and fuel costs) (Fagnant and Kockelman 2015; Taiebat, Stolper, and Xu 2018; Wadud, MacKenzie, and Leiby 2016).

Current studies report a range of estimates for the energy efficiency improvements that CAVs could achieve compared to traditional vehicles, driven by technological enhancements such as optimized driving, eco-routing, congestion reduction, and electrification. While these estimates tend to be optimistic, they vary depending on the assumptions and scope of each study. The magnitude of potential energy savings, however, remains uncertain and is heavily dependent on the pace of technological adoption and behavioral adjustments. Table 1 presents key findings from the literature.

Table 1. Energy-efficiency enhancements enabled by CAVs.

Aspect	Description	Efficiency improvement	Source
Eco-routing	CAVs equipped with real-time traffic data and machine learning algorithms can select routes that minimize fuel consumption and emissions. Eco-routing alone could achieve significant fuel savings depending on traffic conditions and route alternatives.	4% to 20%	Guo et al. (2022)
Impact of platooning	Automated platooning reduces aerodynamic drag by allowing vehicles to travel in tightly spaced groups.	4% to 5% (lead vehicle); 10% to 14% (following vehicles)	Pi et al. (2023)
Fuel savings through congestion reduction	Improved traffic flow via vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication reduces idling and stop-and-go driving in congested areas, contributing to additional energy savings.	V2I connectivity in urban driving: • Improved fuel economy by 6% to 13% for battery electric vehicles (BEVs). • Improved fuel economy by 9% to 15% for fuel-cell electric vehicles (FCEVs). V2V connectivity in highway driving: • Enhanced fuel economy by 5% to 32% for BEVs. • Enhanced fuel economy by 5% to 26% for FCEVs.	Fong, Lane, and Samuelsen (2024)
Improvement in energy efficiency	A commonly cited range for energy efficiency improvements over traditional vehicles. Savings are attributed to smoother driving patterns (e.g., reduced hard braking and acceleration), route optimization, and maintaining constant speeds in free-flowing traffic.	5% to 15% as per the documented road experiments.	Fagnant and Kockelman (2015), Vahidi and Sciarretta (2018), and Faghihian and Sargolzaei (2023)

While energy efficiency improvements remain a core focus of CAVs, their potential benefits extend beyond just fuel savings. One significant advantage is the reduction in travel time costs (TTC), which varies between 25% and 45%, as reported in the literature (International Transport Forum 2018; Victoria Transport Policy Institute 2023). This variation depends on factors such as the purpose of the trip, with work-related or leisure trips benefiting more significantly due to the ability to utilize travel time for productivity or relaxation. However, while these reductions are notable, researchers have reported 60% as the theoretical upper limit for achievable TTC savings (Fagnant and Kockelman 2015; Taiebat, Stolper, and Xu 2018). This ceiling is primarily attributed to the residual in-vehicle attention demands that persist, even with highly advanced levels of automation.

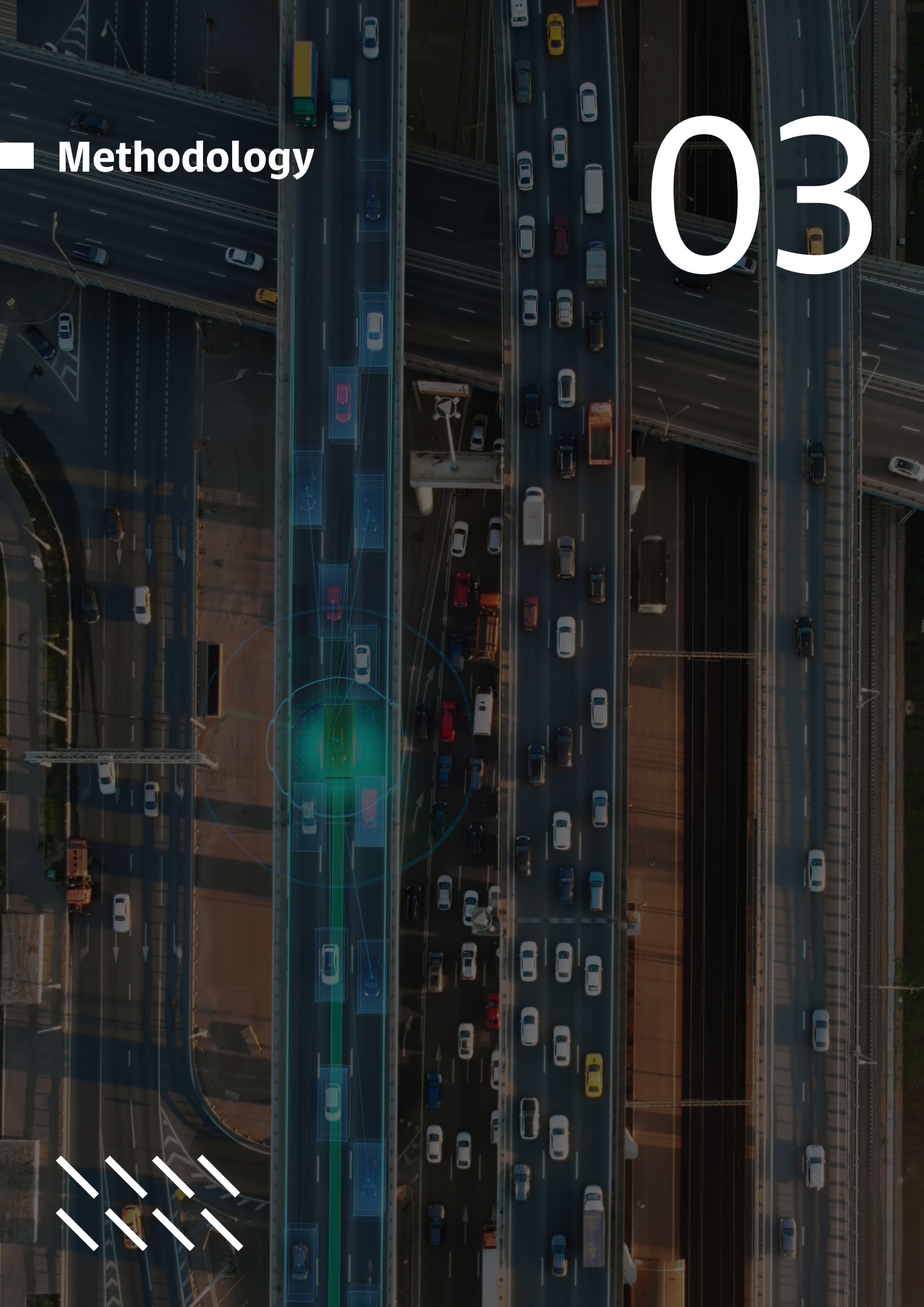
While CAVs have the potential to significantly reduce the cognitive demands of travel – by allowing occupants to engage in work or leisure activities – this benefit is not absolute. Occasional driver intervention remains necessary, particularly under Level 3 and Level 4 automation[1] (Shatnawi, Gonzalez, and Masoud 2025), limiting the full elimination of mental workload. Additionally, drivers may still be required to monitor vehicle operations and respond to unexpected system failures, maintaining a baseline of cognitive engagement. Key findings from the literature highlight the following constraints:

- Partial automation still requires human oversight, especially in transitional scenarios.
- Residual cognitive demand persists due to the need to monitor driving tasks and intervene during failures.
- Maximum travel time cost (TTC) reductions are bounded, with 60% often cited as a theoretical upper limit (Fagnant and Kockelman 2015; Taiebat et al. 2019).
- Perceived benefits vary by use case, with higher impacts on work and leisure-related trips.

These constraints underscore the need for realistic expectations about the benefits of CAVs. Our study builds on this understanding by empirically quantifying how reductions in time and fuel costs influence travel behavior across urban and rural areas and across income levels. This contributes to a deeper understanding of the behavioral rebound effects associated with CAV adoption and informs future transportation and energy policy.

Methodology

03



Methodology

3.1 Data Processing and Descriptive Statistics

To ensure the robustness of our analysis, we processed detailed microdata from the latest National Household Travel Survey (NHTS) dataset, published in 2022 (Federal Highway Administration 2022), which includes over 100,000 trip records from U.S. households.

We extracted information on trip purpose, travel time, distance, household composition, number of vehicles, driver counts, income categories, and urban versus rural classification. This core dataset was augmented with vehicle-specific fuel economy data (miles per gallon, MPG) from the EPA's Fuel Economy database (DOE 2024), matching it with NHTS records based on vehicle make and model (Federal Highway Administration 2009). This integration allowed for the calculation of the average MPG for each household's vehicles, including those with multiple cars. Using the 2022 NHTS trip data, we also derived the average VMT per household.

To enrich the analysis, we incorporated gasoline prices and travel time data from the 2022 NHTS survey. We also included contextual household information, such as household size, the number of trips per household, counts of adults, drivers, and vehicles, as well as area characteristics (e.g., urban vs. non-urban classification). For a more nuanced understanding, we categorized households into six income groups based on reported income ranges in the 2022 NHTS survey, which spanned from less than $25,000 to more than $200,000 annually. These income groups provided a critical dimension for both descriptive and inferential analyses, enabling meaningful comparisons across socioeconomic strata.

The final cleaned dataset comprises 5,115 households (Table 2), including 4,093 urban (Table 5) and 1,022 rural (Table 6) households. Sample sizes for each income group are reported in Tables 7-9. Data cleaning followed three steps: (i) restricting the sample to motorized trips (excluding non-motorized trips such as walking and cycling); (ii) removing households with zero reported VMT (VMT ≤ 0); and (iii) excluding records with undefined fuel cost or efficiency values (e.g., missing values).

Income groups were derived from the 11 NHTS household income levels and consolidated into six categories: 1st income group (levels 1-3: <$24,999); 2nd income group (levels 4-5: $25,000-$49,999); 3rd income group (level 6: $50,000-$74,999); 4th income group (levels 7-8: $75,000-$124,999); 5th income group (level 9: $125,000-$149,999); and 6th income group (levels 10-11: ≥$150,000). For continuous approximations, midpoints were assigned to each income level (e.g., $12,500 for level 2, $20,000 for level 3), and an hourly wage proxy was derived by dividing annual midpoint income by 2,080 working hours.

Following Taiebat et al. (2019) the dependent variable in all our models is the VMT per household. Our analysis focuses on three primary predictors: fuel costs, time costs, and their combined value.

To calculate fuel costs, we used Equation (1):

$$P_f = \frac{\emptyset}{\sum_{i=1}^{n} VMT_j} \sum_{j=1}^{n} \frac{VMT_j}{MPG_j} \quad (1)$$

Where, ø represents the price of gasoline (dollars per gallon), VMT_j is the vehicle miles traveled for the j-th vehicle in a household, and MPG_j is the fuel economy (miles per gallon) of the j-th vehicle.

To compute time costs, we used Equation (2):

$$P_t = \frac{\left(\gamma_w \widehat{w} + \frac{1}{2}\gamma_{NW}\widehat{w}\right) \times \sum T_{vmt}}{\sum_{i=1}^{n} VMT_j} \quad (2)$$

Where, γ_w and γ_{nw} represent wage rates for work-related and non-work-related travel, respectively; $\widehat{w}$ is the average hourly wage; π_{vmt} is the total travel time associated with VMT, and $\sum_{i=1}^{n} VMT_j$ is the total VMT across all vehicles in a household. This equation calculates the per-mile time cost by incorporating both work-related and non-work-related travel time, weighted by their respective wage rates.

In our study, $\widehat{w}$ represents the imputed hourly wage for each household in the dataset, while γ_w and γ_{nw} denote the proportions of work-related and non-work-related trips within a household, respectively. Additionally, we define π_{vmt} as the aggregate cost of fuel and time, calculated as the sum of fuel costs P_f and time costs P_t: $\pi_{vmt} = P_f + P_t$.

The analysis includes both descriptive and inferential components, applied to the entire dataset and stratified across the six identified income groups. This stratification enables a more nuanced examination of the relationships between variables within different income brackets.

Table 2 provides a comprehensive overview of transportation behaviors, time valuation, and household characteristics across six income groups in the United States, along with the national average. Several key patterns emerge:

- **Time allocation differs by income:** The lowest income group (1st) has the highest share of leisure trips (89.3%) and the lowest share of work-related trips (10.7%). In comparison, the 3rd income group shows the highest work-related trip share (17.2%), indicating differing patterns of labor force engagement and time use.

- **Fuel cost and efficiency improve with income:** Fuel cost per city mile decreases from $0.162 in the 1st group to $0.140 in the 6th group, while city fuel economy improves from 25.4 MPG to 30.0 MPG. This suggests that higher-income households have access to more efficient vehicles.

- **Time costs rise steeply with income:** The average time cost per mile increases more than tenfold, from $0.31 in the lowest income group to $3.42 in the highest group, emphasizing the higher opportunity cost of time for affluent households.

- **Higher income equals greater mobility:** Annual VMT increases from 7,782 miles in the 1st group to nearly 20,000 miles in the 6th group. Similarly, the number of trips rises from 4.2 to 6.5 per day, and vehicle ownership climbs from 1.5 to 2.5 vehicles per household.

- **Larger and better-resourced households:** Household size increases from 2.35 to about 2.94 people, and the number of drivers and adults per household grows with income, highlighting broader resource availability.

The same analysis was conducted to compare urban and rural households across income groups (see Table 3), revealing clear differences in travel behavior and household characteristics.

- **Fuel efficiency is higher in urban settings**: In most income groups, urban households exhibit slightly better fuel economy. For instance, in the 6th income group, the average city MPG is 30.2 in urban areas vs. 29.1 in rural areas, and highway MPG is 42.2 vs. 40.8, respectively.

- **Time costs per mile are consistently higher in urban areas:** For the highest income group, urban households face an average time cost of $3.64 per mile, compared to $2.26 in rural areas, reflecting higher opportunity costs of time in cities.

- **Rural households drive more:** Annual VMT in the 6th income group is 24,375 miles in rural areas vs. 19,134 miles in urban ones. This trend is consistent across all income brackets, underscoring rural reliance on personal vehicles.

- **Larger and more vehicle-rich rural households:** Rural households tend to be larger and have higher vehicle ownership, particularly in second to fifth income groups. For example, in the 5th income group, rural households average 3.13 people compared to 2.99 in urban areas and own more vehicles (2.96 versus 2.44).

- **Trip-making varies by setting and income:** Urban households generally take more trips than rural households, especially at the lowest (4.41 versus 3.60) and highest (6.63 versus 5.73) income groups. However, rural households surpass urban ones in the middle-income categories, the 3rd (5.07 versus 4.60) and 4th (6.0 versus 5.7) groups.

- **Fuel costs show moderate differences:** Fuel cost per city mile in the 1st income group is slightly higher in urban households ($0.164) than in rural ones ($0.157), with the gap narrowing in higher-income groups.

These quantified comparisons confirm that urban households prioritize efficiency and time. In contrast, rural households prioritize access and coverage, leading to distinct energy and travel demand profiles across geographies and income groups.

Table 2. Descriptive statistics – general (mean and standard deviation).

Attribute	U.S. average	1st income group	2nd income group	3rd income group	4th income group	5th income group	6th income group
Work share	0.154	0.107	0.151	0.172	0.162	0.158	0.147
	(0.004)	(0.016)	(0.011)	(0.011)	(0.008)	(0.009)	(0.012)
Leisure share	0.846	0.893	0.849	0.828	0.838	0.842	0.853
	(0.004)	(0.016)	(0.011)	(0.011)	(0.008)	(0.009)	(0.012)
Fuel cost ($/mile) (city)	0.144	0.162	0.146	0.144	0.141	0.143	0.140
	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Fuel cost ($/mile)	0.100	0.110	0.101	0.100	0.097	0.100	0.098
(highway)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Average time cost ($/mile)	1.522	0.314	0.678	1.072	1.455	2.194	3.415
	(0.033)	(0.023)	(0.025)	(0.112)	(0.041)	(0.056)	(0.142)
Annual VMT (miles)	15280	7782	10843	14870	16025	19177	19968
	(483)	(682)	(916)	(1232)	(770)	(1596)	(1525)
Annual driving time	494.258	313.936	387.005	453.233	515.560	602.178	621.777
(hours)	(10.237)	(19.813)	(20.897)	(23.497)	(17.398)	(29.937)	(36.765)
Fuel economy (MPG)	28.678	25.397	27.944	28.969	28.929	29.403	30.043
(city)	(0.121)	(0.409)	(0.308)	(0.321)	(0.203)	(0.268)	(0.380)
Fuel economy (MPG)	40.411	36.760	39.596	40.611	40.759	41.204	41.948
(highway)	(0.121)	(0.444)	(0.310)	(0.315)	(0.200)	(0.271)	(0.351)
Gas price	4.076	4.015	3.970	4.066	4.055	4.146	4.219
($/gallon)	(0.012)	(0.045)	(0.032)	(0.033)	(0.024)	(0.033)	(0.041)
Household size	2.642	2.354	2.432	2.443	2.629	3.008	2.937
(people)	(0.028)	(0.121)	(0.073)	(0.073)	(0.047)	(0.063)	(0.064)
Number of trips per household	5.397	4.225	4.421	4.699	5.742	6.362	6.485
	(0.079)	(0.336)	(0.143)	(0.164)	(0.152)	(0.196)	(0.251)
Count of adults	2.007	1.675	1.827	1.891	2.016	2.299	2.198
	(0.016)	(0.059)	(0.040)	(0.037)	(0.024)	(0.044)	(0.039)
Count of drivers	1.932	1.508	1.658	1.824	1.965	2.265	2.186
	(0.015)	(0.052)	(0.035)	(0.039)	(0.024)	(0.039)	(0.037)
Count of vehicles	2.113	1.512	1.713	2.019	2.175	2.513	2.476
	(0.021)	(0.056)	(0.040)	(0.058)	(0.042)	(0.051)	(0.053)
Urban areas	0.805	0.777	0.801	0.787	0.785	0.857	0.841
(1=urban; 0=rural)	(0.006)	(0.026)	(0.018)	(0.017)	(0.013)	(0.014)	(0.019)

Table 3. Descriptive statistics – urban and rural (mean and standard deviation).

Attribute	1st income group		2nd income group		3rd income group		4th income group		5th income group		6th income group	
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Work share	0.111	0.093	0.153	0.140	0.176	0.157	0.153	0.194	0.151	0.196	0.147	0.147
	(0.019)	(0.026)	(0.012)	(0.022)	(0.012)	(0.019)	(0.009)	(0.020)	(0.010)	(0.025)	(0.013)	(0.031)
Leisure share	0.889	0.907	0.847	0.860	0.824	0.843	0.847	0.806	0.849	0.804	0.853	0.853
	(0.019)	(0.026)	(0.012)	(0.022)	(0.012)	(0.019)	(0.009)	(0.020)	(0.010)	(0.025)	(0.013)	(0.031)
Fuel cost ($/mile) (city)	0.164	0.157	0.146	0.148	0.145	0.142	0.140	0.142	0.142	0.147	0.140	0.141
	(0.004)	(0.005)	(0.003)	(0.004)	(0.002)	(0.005)	(0.002)	(0.003)	(0.002)	(0.005)	(0.003)	(0.007)
Fuel cost ($/mile) (highway)	0.111	0.105	0.100	0.102	0.100	0.099	0.098	0.097	0.100	0.101	0.098	0.097
	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)
Average time cost ($/mile)	0.344	0.211	0.704	0.573	1.185	0.653	1.574	1.018	2.304	1.535	3.635	2.255
	(0.028)	(0.027)	(0.025)	(0.077)	(0.141)	(0.029)	(0.049)	(0.051)	(0.062)	(0.094)	(0.163)	(0.132)
Annual VMT (miles)	7275	9543	9070	17987	12887	22191	14435	21828	18534	23016	19134	24375
	(780)	(1393)	(753)	(3366)	(1362)	(2746)	(853)	(1708)	(1801)	(2832)	(1642)	(3982)
Annual driving time (hours)	311.09	323.79	359.75	496.84	419.60	577.38	489.01	612.41	597.59	629.59	622.06	620.27
	(23.11)	(37.62)	(19.58)	(68.47)	(24.51)	(60.87)	(19.47)	(37.78)	(33.21)	(64.93)	(39.59)	(98.01)
Fuel economy (MPG) (city)	25.308	25.709	28.082	27.388	28.986	28.907	29.278	27.658	29.745	27.357	30.231	29.051
	(0.463)	(0.865)	(0.334)	(0.758)	(0.359)	(0.714)	(0.233)	(0.414)	(0.294)	(0.598)	(0.392)	(1.164)
Fuel economy (MPG) (highway)	36.568	37.428	39.793	38.801	40.693	40.309	41.104	39.501	41.551	39.131	42.173	40.761
	(0.494)	(0.981)	(0.335)	(0.778)	(0.357)	(0.667)	(0.229)	(0.407)	(0.294)	(0.676)	(0.369)	(1.007)

Table 3. Continued

Attribute	1st income group		2nd income group		3rd income group		4th income group		5th income group		6th income group	
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Gas price ($/gallon)	4.058	3.866	3.975	3.948	4.075	4.031	4.074	3.984	4.154	4.095	4.234	4.141
	(0.054)	(0.069)	(0.037)	(0.061)	(0.037)	(0.073)	(0.028)	(0.049)	(0.036)	(0.072)	(0.045)	(0.098)
Household size (people)	2.387	2.237	2.405	2.541	2.348	2.793	2.575	2.829	2.987	3.134	2.967	2.781
	(0.142)	(0.221)	(0.079)	(0.181)	(0.081)	(0.160)	(0.053)	(0.098)	(0.070)	(0.127)	(0.071)	(0.146)
Number of trips per household	4.406	3.598	4.443	4.329	4.598	5.072	5.669	6.008	6.444	5.874	6.628	5.728
	(0.421)	(0.313)	(0.153)	(0.374)	(0.167)	(0.453)	(0.168)	(0.344)	(0.215)	(0.466)	(0.273)	(0.624)
Count of adults	1.675	1.674	1.806	1.908	1.840	2.080	1.986	2.123	2.296	2.314	2.218	2.093
	(0.070)	(0.103)	(0.044)	(0.092)	(0.040)	(0.089)	(0.029)	(0.044)	(0.050)	(0.061)	(0.044)	(0.071)
Count of drivers	1.487	1.580	1.624	1.795	1.741	2.130	1.928	2.101	2.249	2.365	2.192	2.155
	(0.060)	(0.102)	(0.039)	(0.077)	(0.041)	(0.090)	(0.028)	(0.044)	(0.044)	(0.067)	(0.041)	(0.086)
Count of vehicles	1.454	1.712	1.664	1.911	1.902	2.452	2.020	2.740	2.439	2.961	2.412	2.812
	(0.059)	(0.134)	(0.044)	(0.090)	(0.067)	(0.103)	(0.034)	(0.137)	(0.056)	(0.127)	(0.056)	(0.155)

3.2 Methodology: Modeling VMT Response to Travel Costs

This section presents the empirical modeling framework used to estimate how household VMT responds to changes in travel-related costs – specifically, per-mile fuel costs and time costs. We build upon the econometric structure proposed by Taiebat et al. (2019), which models VMT as a function of the time-inclusive marginal cost of travel. Our study extends this framework by applying it across different household income groups and geographic settings (urban vs. rural), enabling a disaggregated assessment of energy rebound effects under varying socioeconomic conditions. All models discussed in this subsection are estimated using generalized least squares (GLS) regression to account for heteroskedasticity and to incorporate the sampling weights provided by the NHTS dataset, ensuring consistent and unbiased coefficient estimates.

3.2.1 Theoretical Framework and Functional Form

Following Taiebat et al. (2019) to estimate the impact of the time-inclusive marginal cost of travel (π_{vmt}) on VMT, we use the following specifications:

$$Ln(VMT) = \alpha_0 + \alpha_1 Ln(\pi_{vmt}) \tag{3}$$

Where, P_f is the per-mile fuel cost of VMT and P_t is the cost of time spent on VMT and

$$\pi_{vmt} = P_f + P_t \tag{4}$$

To estimate the individual impacts of fuel and time costs on VMT, we link VMT directly to these two variables via Equation (3). Using Equation (4), the following relationship can be written:

$$Ln(VMT) = Ln(P_f + P_t) \tag{5}$$

Applying Taylor expansion to the right-hand side of Equation (5) up to second-order derivatives, about the point (a, b), gives us the following:

$$Ln(P_f + P_t) \approx \ln(a+b) + \frac{1}{a+b}[(P_f - a) + (P_f - b)] - \frac{1}{2(a+b)^2}[(P_f - a)^2 + 2(P_f - a)(P_t - b) + (P_t - b)^2] \tag{6}$$

Then, dropping higher-order and cross-product terms and making some simplifications, Equation (6) can be expressed as follows:

$$Ln(VMT) = a_0 + a_1 P_f + a_2 P_t \tag{7}$$

Then, considering the relationship between the functions $f(x) = x$ *and* $g(x) = Ln(x)$ through the Taylor expansion leaves us with the following formula:

$$Ln(VMT) = b_0 + b_1 Ln(P_f) + b_2 Ln(P_t) \tag{8}$$

Equation (8) corresponds to Model 3 in Taiebat et al. (2019). The existence of quadratic terms of fuel and time cost in equation (6) raises a potential non-linear relationship between these two costs and VMT. The existence of a non-linear (quadratic) relationship can be tested using the following simplified specification:

$$Ln(VMT) = c_0 + c_1 Ln(P_f) + c_2 (Ln(P_f))^2 + c_3 Ln(P_t) + c_4 (Ln(P_t))^2 \tag{9}$$

If $c_2 = c_4 = 0$, then equation (9) reduces to Equation (8). In cases where only $c_2 = 0$ ($c_4 = 0$) model (9) becomes non-linear only with respect to P_t (P_f). The same potential non-linearity applies to the specification where we have π_{vmt} as a left-hand side variable:

$$Ln(VMT) = d_0 + d_1 Ln(\pi_{vmt}) + d_2 (Ln(\pi_{vmt}))^2 \tag{10}$$

Analogically, if $d_2 = 0$, then model (10) reduces to a linear specification (3).

Considering the discussions above, we utilize a general-to-specific modeling approach, starting with a non-linear case to select the most appropriate model. In other words, we begin with specifications (9) and (10) and test them to select the relevant model.

3.2.2 Empirical Model Specifications

For econometric modeling purposes, the following model specifications will be used.

$$\textit{Model 1:}\quad \begin{aligned} Ln(VMT_i) &= \delta_0 + \delta_1 Ln(P_{f,i}) + \delta X_i + \varepsilon_{1,i} \\ Ln(VMT_i) &= \delta'_0 + \delta'_1 Ln(P_{f,i}) + \delta'_2 (Ln(P_{f,i}))^2 \\ &\quad + \delta' X_i + \varepsilon_{2,i} \end{aligned} \tag{11}$$

Model 2:

$$Ln(VMT_i) = \varepsilon_0 + \varepsilon_1 Ln(P_{t,i}) + \varepsilon X_i + \varepsilon_{3,i}$$
$$Ln(VMT_i) = \varepsilon'_0 + \varepsilon'_1 Ln(P_{t,i}) + \varepsilon'_2 (Ln(P_{t,i}))^2 + \varepsilon' X_i + \varepsilon_{4,i} \quad (12)$$

Model 3:

$$Ln(VMT_i) = \theta_0 + \theta_1 Ln(P_{f,i}) + \theta_2 Ln(P_{t,i}) + \theta X_i + \varepsilon_{5,i}$$
$$Ln(VMT_i) = \theta'_0 + \theta'_1 Ln(P_{f,i}) + \theta'_2 (Ln(P_{f,i}))^2 + \theta'_3 Ln(P_{t,i}) + \theta'_4 (Ln(P_{t,i}))^2 + \theta' X_i + \varepsilon_{6,i} \quad (13)$$

Model 4:

$$Ln(VMT_i) = \vartheta_0 + \vartheta_1 Ln(\pi_{vmt,i}) + \vartheta X_i + \varepsilon_{7,i}$$
$$Ln(VMT_i) = \vartheta'_0 + \vartheta'_1 Ln(\pi_{vmt,i}) + \vartheta'_2 (Ln(\pi_{vmt,i}))^2 + \vartheta' X_i + \varepsilon_{8,i} \quad (14)$$

Model (13) nests Models (11) and (12). All variables are defined above; X incorporates all control variables, characterizing households. $\varepsilon_{j,i}$ is an error term and numbered to specify different error series across models. The parameters in front of the variables are coefficients to be estimated econometrically, and these are differentiated by different letters and prime signs ($'$) across models. In addition to the general case, we have estimated models for the urban and rural areas separately to determine if there are any differences in consumers' behaviors in these two areas. Each model is estimated via generalized least squares (GLS) regression, utilizing the sampling weights provided by the NHTS.

3.2.3 Relative Energy Demand

The formula used in our analysis estimates the relative energy demand (RED) as a function of changes in fuel economy and time costs, incorporating the elasticity of VMT with respect to travel costs. The following steps provide a detailed step-by-step explanation of the formula and its derivation, highlighting how changes in these parameters influence travel behavior.

Building on this foundation, the forecasting analysis examines the energy and travel demand rebounds associated with CAV adoption. Specifically, it evaluates how variations in fuel economy (denoted as MPG) and travel time cost (denoted as P_t) affect VMT. To capture these dynamics, we simulate changes in fuel economy and time costs using the variables r_1 and r_2, respectively.

Here:

$r_1 \in [0.0, 0.4]$	indicates fuel economy improvements ranging from 0% to 40%.
$r_2 \in [0.0, 0.45]$	indicates travel time cost reductions ranging from 0% to 45%.

The key metric of interest is the change in VMT, expressed as a percentage difference compared to the pre-CAV business-as-usual (BAU) scenario. The following provides a detailed, step-by-step explanation of how the rebound effect from CAV adoption is estimated in terms of VMT and energy demand.

Step 1: Initial Cost Per Mile (Baseline Travel Cost, BTC)

The baseline travel cost (BTC) per mile (see Equation (15)) represents the initial cost incurred by drivers and is the sum of Fuel cost per mile $= \frac{Fuel\ cost}{Fuel\ Economy}$ and the time cost per mile (*TCT*).

$$BTC = \frac{Fuel\ cost}{Fuel\ Economy} + TCT \quad (15)$$

Where: fuel cost is expressed as the cost of fuel per gallon ($/gal), fuel economy is measured in miles per gallon (MPG), and TCT represents the time cost per mile ($/mile).

Step 2: Adjusted Travel Cost (ATC)

When fuel economy increases by r_1% and time cost decreases by r_2% the adjusted travel cost (ATC) is expressed as (16):

$$ATC\ (X, Y) = \frac{Fuel\ cost}{(1 + r_1) * Fuel\ Economy} + (1 - r_2) * TCT \quad (16)$$

Where: $\frac{Fuel\ cost}{(1 + r_1) * Fuel\ Economy}$ and $(1 - r_2) * TCT$ are the fuel cost per mile and the time cost per mile after CAV adoption, respectively.

$1 + r_1$	reflects an r_1% increase in fuel economy (reducing cost per mile)
$1 - r_2$	reflects a r_2% decrease in time cost (improving travel efficiency).

Step 3: Relative Energy Demand

The *RED* measures the percentage change in energy consumption, assuming it is proportional to VMT changes, see Equation (17).

$$RED = \frac{\text{VMT}_{CAV} - \text{VMT}_{baseline}}{\text{VMT}_{baseline}} = \frac{\text{VMT}_{CAV}}{\text{VMT}_{baseline}} - 1 \quad (17)$$

Considering that $\widehat{VMT} = e^{\hat{\theta}_0} P_f^{\hat{\theta}_1} P_t^{\hat{\theta}_2}$ from the estimated exponential version of linear Model 3, and assuming there is no change in the fuel cost, we can derive the following Equation (18):

$$RED = \frac{\text{VMT}_{CAV}}{\text{VMT}_{baseline}} - 1 = \frac{e^{\hat{\theta}_0} P_{f,CAV}^{\hat{\theta}_1} P_{t,CAV}^{\hat{\theta}_2}}{e^{\hat{\theta}_0} P_{f,baseline}^{\hat{\theta}_1} P_{t,baseline}^{\hat{\theta}_2}} - 1$$

$$= \left(\frac{P_{f,CAV}}{P_{f,baseline}}\right)^{\hat{\theta}_1} \left(\frac{P_{t,CAV}}{P_{t,baseline}}\right)^{\hat{\theta}_2} - 1 \quad (18)$$

$$= \left(\frac{\frac{Fuel\ cost}{(1 + r_1)\ Fuel\ Economy}}{\frac{Fuel\ cost}{Fuel\ Economy}}\right)^{\hat{\theta}_1} \left(\frac{(1 - r_2)\ TCT}{TCT}\right)^{\hat{\theta}_2} - 1$$

Simplifying Equation (18), we end up with

$$RED = \left(\frac{1}{(1 + r_1)}\right)^{\hat{\theta}_1} ((1 - r_2))^{\hat{\theta}_2} - 1 \quad (19)$$

Where: $\hat{\theta}_1$ = Elasticity due to fuel cost changes via fuel economy improvement, $\hat{\theta}_2$ = Elasticity due to time cost changes, $1 + r_1$ reflects an r_1% increase in fuel economy (reducing cost per mile) and 1- r_2 reflects a r_2% decrease in time cost (improving travel efficiency).

Results and Discussion

04



Results and Discussion

4.1 Empirical Results

Table 4 presents the estimation results for the models in which the coefficients for fuel and time costs were found to be statistically significant. In this context, specification refers to the functional form used in the estimation – either linear or log-linear (log-log) – which defines how VMT responds to changes in fuel and time costs.

Each of these model forms was estimated, and only those yielding statistically significant coefficients are reported in Table 4. Estimation results for the pooled (general) sample appear in Table 4, while Table 5 and Table 6 present results disaggregated by urban and rural areas, respectively.

Table 4. Elasticity estimation across various models – general context.

Variable	Model 1	Model 2	Model 3	Model 4
log (fuel cost)	-0.366 ***		-0.337 ***	
	0.038		0.034	
$(\log(\text{fuel cost}))^2$				
log (time cost)		-0.569 ***	-0.565 ***	
		0.016	0.016	
$(\log(\text{time cost}))^2$		-0.139 ***	-0.137 ***	
		0.011	0.010	
log(time-inclusive cost)				-0.593 ***
				0.020
$(\log(\text{time-inclusive cost}))^2$				-0.145 ***
				0.016
Intercept	7.352 ***	7.794 ***	7.087 ***	7.863 ***
	0.098	0.055	0.089	0.054
Household size	-0.082 ***	-0.115 ***	-0.111 ***	-0.114 ***
	0.015	0.014	0.014	0.014
Household trips	0.120 ***	0.125 ***	0.122 ***	0.125 ***
	0.004	0.004	0.004	0.004
Drivers in the household	0.099 **	0.173 ***	0.156 ***	0.169 ***
	0.031	0.028	0.028	0.028
Vehicles in household	0.117 ***	0.134 ***	0.140 ***	0.135 ***
	0.018	0.016	0.016	0.016
Household in urban/rural area	-0.473 ***	-0.200 ***	-0.198 ***	-0.197 ***
	0.041	0.038	0.037	0.037
Workers in household	0.144 ***	0.262 ***	0.255 ***	0.263 ***
	0.021	0.019	0.019	0.019
Observations	5115	5115	5115	5115
Adjusted R^2	0.255	0.391	0.403	0.395
AIC	17258.0	16227.1	16130.6	16200.8
BIC	17316.9	16292.5	16202.5	16266.2

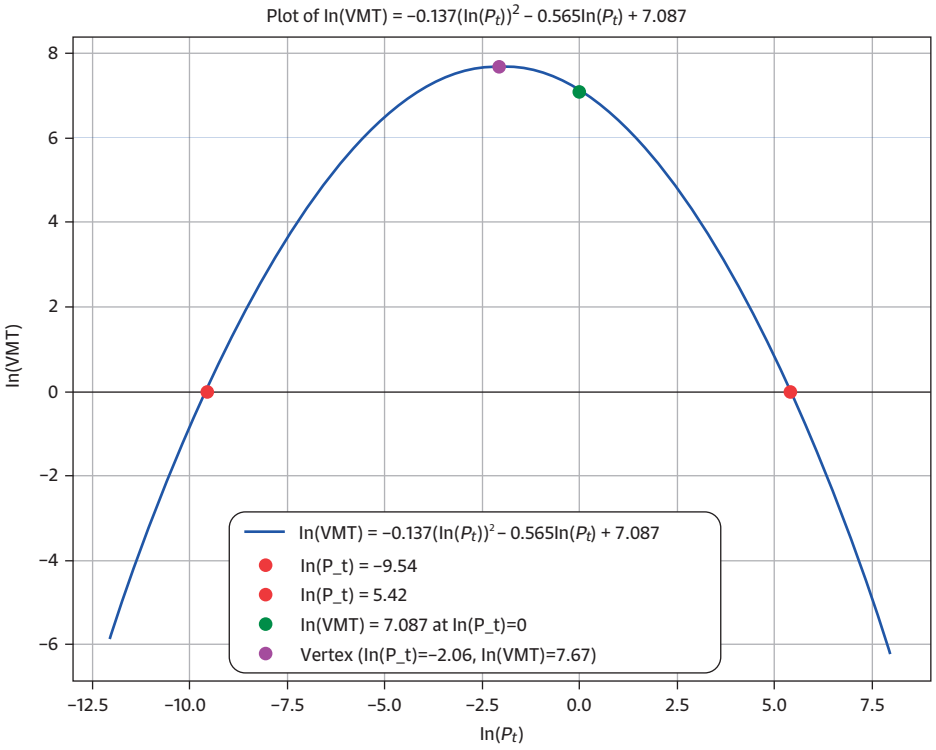
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Based on the estimation results given in Table 4, the model selection criteria – specifically the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) – indicate a preference for Model 3. This is because Model 3 exhibits lower AIC and BIC values compared to Models 1, 2, and 4, signaling a better overall fit to the data while penalizing model complexity. In terms of coefficient estimates, Model 3 captures the effects of both fuel cost and time cost jointly, whereas Models 1 and 2 estimate these effects separately, and Model 4 assesses the combined impact. This integration allows for a more complete representation of the travel cost burden.

Moreover, the quadratic term for time cost is statistically significant in Model 3 (coefficient ≈ 0.137, $p < 0.001$), suggesting a non-linear relationship between time cost and VMT, which Models 1 and 2 partially overlook. The signs of the estimated coefficients are consistent with economic expectations: both fuel and time costs have negative elasticities, indicating that VMT decreases as travel costs increase. The estimated fuel cost elasticity is approximately -0.337 in the preferred model, while the non-linear form of time cost elasticity provides a more flexible and realistic depiction of behavioral response.

Geometrically, this non-linearity is illustrated in Figure 1, which plots the relationship between VMT and time cost using the results from Model 3.

Figure 1. Non-linear relationship between time cost and VMT.



Source: Authors.

The validity of the quadratic relationship is subject to the condition of the turning point being within the boundaries of the sample values (Hasanov, Hunt, and Mikayilov 2021) of the related explanatory variable, time cost in our case. Based on information provided in the 3.1 Data Processing and Descriptive Statistics section and findings in Figure 1, we see that this condition is met. Therefore, we conclude that the relationship between time cost and VMT demonstrates a U-shaped form as shown in Figure 1. Using the elasticity formula, one can obtain the corresponding elasticity (from the second equation of Model 3) to be:

$$E_{Pt} = \theta'_3 + 2\theta'_4 Ln(P_{t,i}) \quad (20)$$

Applying the estimation results in Table 4 (Model 3), we end up with:

$$E_{Pt} = -0.565 - 2 * (-0.137) * Ln(P_{t,i}) = -0.565 - 0.274 * Ln(P_{t,i}) \quad (21)$$

The time cost (price) elasticity of VMT, as in Equation (21), indicates that households respond to changes in time cost non-linearly. Specifically, the elasticity in Equation (21) implies that *i*) time cost negatively impacts VMT and *ii*) an additional increase in time cost makes households more responsive, further reducing driving distance.

Table 5. Elasticity estimation across various models – urban context.

Variable	Model 1	Model 2	Model 3	Model 4
log (fuel cost)	-0.086		-0.323 ***	
	0.158		0.037	
log (fuel cost)^2	0.049			
	0.029			
log (time cost)		-0.560 ***	-0.558 ***	
		0.018	0.018	
(log (time cost))^2		-0.132 ***	-0.130 ***	
		0.012	0.012	
log(time-inclusive cost)				-0.597 ***
				0.025
(log(time-inclusive cost))^2				-0.133 ***
				0.018
Intercept	7.305 ***	7.588 ***	6.969 ***	7.672 ***
	0.206	0.046	0.085	0.045
Household size	-0.068 ***	-0.104 ***	-0.098 ***	-0.103 ***
	0.018	0.016	0.016	0.016
Household trips	0.119 ***	0.126 ***	0.122 ***	0.125 ***
	0.005	0.004	0.004	0.004
Drivers in the household	0.078 *	0.159 ***	0.140 ***	0.154 ***
	0.036	0.032	0.032	0.032
Vehicles in household	0.116 ***	0.128 ***	0.137	0.131 ***
	0.022	0.020	0.020	0.020
Workers in household	0.144 ***	0.266 ***	0.261 ***	0.268 ***
	0.023	0.021	0.021	0.021
Observations	4093	4093	4093	4093
Adjusted R^2	0.23	0.377	0.389	0.382
AIC	13886.6	13016.2	12943.7	12989.4
BIC	13943.5	13073.1	13006.9	13046.2

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

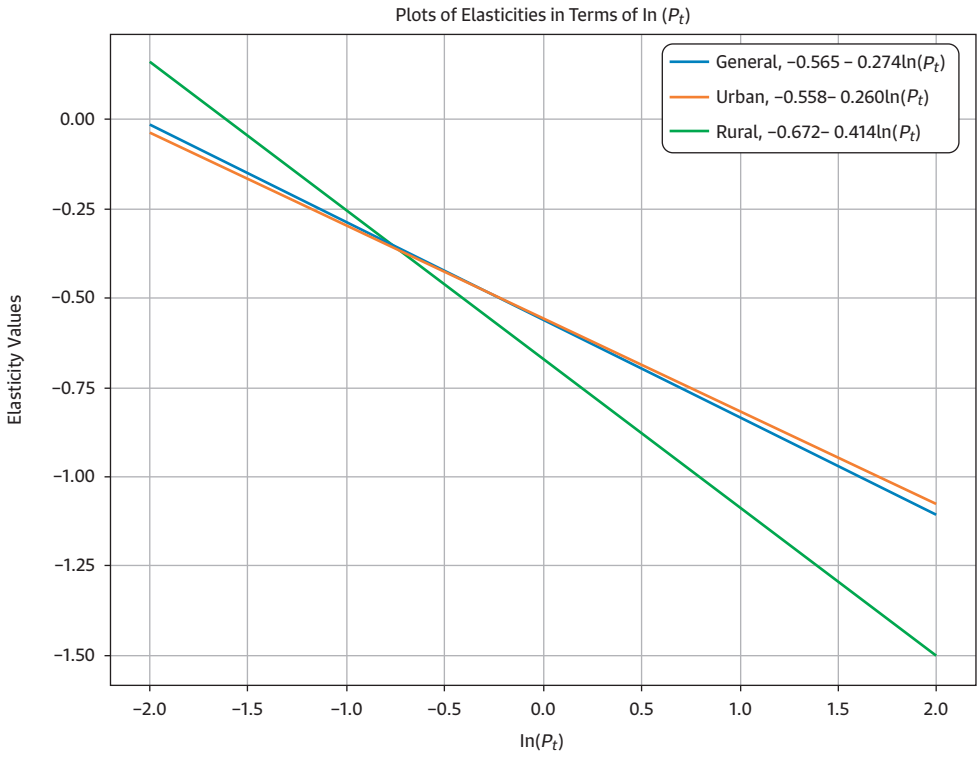
Table 6. Elasticity estimation across various models – rural context.

Variable	Model 1	Model 2	Model 3	Model 4
log (fuel cost)	-0.428 ***		-0.386 ***	
	0.079		0.072	
(log (fuel cost))^2				
log (time cost)		-0.683 ***	-0.672 ***	
		0.048	0.047	
(log (time cost))^2		-0.213 ***	-0.207 ***	
		0.029	0.028	
log(time-inclusive cost)				-0.685 ***
				0.047
(log(time-inclusive cost))^2				-0.269 ***
				0.044
Intercept	7.086 ***	7.825 ***	6.948 ***	7.912 ***
	0.207	0.104	0.193	0.105
Household size	-0.145 ***	-0.159 ***	-0.159 ***	-0.157 ***
	0.033	0.030	0.030	0.030
Household trips	0.123 ***	0.122 ***	0.121 ***	0.122 ***
	0.008	0.008	0.008	0.008
Drivers in the household	0.200 **	0.228 ***	0.218 ***	0.226 ***
	0.065	0.060	0.060	0.060
Vehicles in household	0.115 ***	0.148 ***	0.150 ***	0.147 ***
	0.029	0.027	0.027	0.027
Workers in household	0.152 ***	0.248 ***	0.235 ***	0.247 ***
	0.044	0.041	0.041	0.041
Observations	1022	1022	1022	1022
Adjusted R^2	0.272	0.377	0.394	0.381
AIC	3369.5	3211.4	3184.9	3205.5
BIC	3408.9	3255.8	3234.2	3249.8

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Model 3 was also selected for both rural and urban areas based on the selection criteria (see Tables 5 and 6). The impact of fuel cost is found to be higher for rural households. The time cost elasticities for the general, urban, and rural household cases are demonstrated in Figure 2. As can be seen from Figure 2, the elasticity for households living in rural areas is larger (i.e., more negative) than that of their urban counterparts. This finding aligns with economic reasoning, as households in rural areas tend to drive more, making an increase in time costs more significant for them.

Figure 2. Time cost elasticities of VMT.



Source: Authors.

Table 7 presents the estimation results across different income groups. We have estimated all models across income groups, and the results are presented in Appendix Table A1, Table A2, and Table A3. Table 7 only presents the results of the selected models. Table 8 and Table 9 present the results of estimations across income groups for urban and rural areas, respectively.

As can be seen from Table 7, the time cost elasticity of VMT is higher for households with higher income levels. The same result holds for households living in rural and urban areas. The fuel cost elasticity also changes across groups; however, it is difficult to identify a consistent pattern in any case. The time cost elasticity follows a non-linear trajectory across income groups in both urban and rural areas. However, it is challenging to make a general statement regarding which households experience a higher magnitude of elasticity across income groups.

Table 7. Elasticity estimation by income group – general context.

Variable	1st income group		2nd income group		3rd income group		4th income group		5th income group		6th income group	
	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4
log (fuel cost)	-0.191		-0.430 ***		-0.289 ***		-0.166 ***		-0.233 ***		0.094	
	0.129		0.067		0.066		0.047		0.061		0.067	
log (time cost)	-0.835 ***		-1.280 ***		-1.376 ***		-1.423 ***		-1.504 ***		-1.504 ***	
	0.060		0.042		0.039		0.035		0.046		0.058	
log(time-inclusive cost)		-1.286 ***		-1.574 ***		-1.579 ***		-1.568 ***		-1.606 ***		-1.557 ***
		0.087		0.052		0.044		0.038		0.049		0.061
Intercept	6.247 ***	6.592 ***	5.829 ***	6.939 ***	7.036 ***	7.872 ***	7.819 ***	8.376 ***	8.701 ***	9.397 ***	9.960 ***	9.892 ***
	0.300	0.154	0.159	0.078	0.153	0.062	0.117	0.063	0.159	0.083	0.175	0.101
Household size	-0.048		-0.086 ***	-0.095 ***	-0.079 ***	-0.078 ***	-0.051 *	-0.046 *	-0.054 *	-0.054 *		
	0.034		0.025	0.025	0.022	0.022	0.021	0.021	0.022	0.023		
Household trips	0.126 ***	0.112 ***	0.130 ***	0.129 ***	0.137 ***	0.135 ***	0.097 ***	0.097 ***	0.087 ***	0.087 ***	0.111 ***	0.109 ***
	0.013	0.012	0.009	0.009	0.008	0.008	0.005	0.005	0.006	0.006	0.007	0.007
Drivers in the household			0.117 *	0.131 *			0.143 ***	0.137 ***				
			0.052	0.053			0.042	0.042				
Vehicles in household			0.094 **	0.096 **	0.065 **	0.060 *	0.052 *	0.051 *	0.076 **	0.073 **		
			0.036	0.037	0.024	0.024	0.023	0.023	0.024	0.024		
Households in urban/rural areas	-0.240 *	-0.207										
	0.116	0.115										
Workers in household	0.141 *	0.104	0.184 ***	0.189 ***	0.187 ***	0.198 ***	0.138 ***	0.139 ***	0.158 ***	0.157 ***	0.154 ***	0.153 ***
	0.066	0.062	0.038	0.038	0.033	0.033	0.026	0.026	0.031	0.031	0.039	0.039
Observations	363	363	830	830	903	903	1489	1489	943	943	587	587
Adjusted R^2	0.486	0.5	0.63	0.615	0.665	0.66	0.634	0.634	0.621	0.617	0.639	0.635
AIC	1075.2	1063.5	2213.2	2243.9	2345.7	2359.8	3924.0	3924.9	2397.7	2406.9	1525.2	1529.9
BIC	1106.4	1086.8	2255.7	2281.6	2384.1	2393.4	3971.7	3967.4	2436.5	2440.8	1551.4	1551.8

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8. Elasticity estimation by income group – urban context.

Variable	1st income group		2nd income group		3rd income group		4th income group		5th income group		6th income group	
	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4
log (fuel cost)	-0.163		-0.416 ***		-0.293 ***		-0.153 **		-0.161 *		0.110	
	0.136		0.066		0.072		0.053		0.065		0.077	
log (time cost)	-0.893 ***		-1.240 ***		-1.371 ***		-1.430 ***		-1.546 ***		-1.488 ***	
	0.064		0.048		0.044		0.038		0.050		0.064	
log(time-inclusive cost)		-1.367 ***		-1.561 ***		-1.569 ***		-1.588 ***		-1.665 ***		-1.557 ***
		0.097		0.060		0.051		0.042		0.053		0.067
Intercept	5.952 ***	6.438 ***	5.977 ***	7.013 ***	7.023 ***	7.852 ***	7.888 ***	8.427 ***	8.989 ***	9.524 ***	10.035 ***	9.984 ***
	0.273	0.137	0.147	0.076	0.156	0.070	0.121	0.067	0.162	0.090	0.184	0.116
Household size	-0.087 *	-0.075			-0.088 ***	-0.082 ***	-0.054 *	-0.048 *	-0.050 *	-0.063 *		
	0.039	0.042			0.025	0.026	0.024	0.024	0.024	0.027		
Household trips	0.126 ***	0.113 ***	0.122 ***	0.120 ***	0.144 ***	0.143 ***	0.104 ***	0.104 ***	0.082 ***	0.082 ***	0.108 ***	0.105 ***
	0.014	0.014	0.010	0.010	0.010	0.010	0.006	0.006	0.006	0.006	0.008	0.007
Drivers in the household		0.146					0.182 ***	0.173 ***		0.082		
		0.083					0.042	0.042		0.046		
Vehicles in household	0.112		0.093 **	0.099 **	0.048	0.042			0.049			
	0.066		0.035	0.036	0.027	0.028			0.027			
Households in urban areas	0.126		0.169 ***	0.176 ***	0.256 ***	0.264 ***	0.125 ***	0.124 ***	0.173 ***	0.155 ***	0.128 **	0.130 **
	0.077		0.039	0.039	0.039	0.039	0.029	0.029	0.033	0.037	0.042	0.043
Workers in household	-0.163		-0.416 ***		-0.293 ***		-0.153 **		-0.161 *		0.110	
	0.136		0.066		0.072		0.053		0.065		0.077	
Observations	271	271	667	667	699	699	1166	1166	796	796	494	494
Adjusted R^2	0.524	0.527	0.616	0.599	0.663	0.652	0.644	0.644	0.628	0.625	0.634	0.63
AIC	797.0	793.3	1730.6	1757.9	1813.7	1834.6	3023.5	3024.3	2024.3	2029.0	1287.5	1292.3
BIC	825.8	814.9	1762.1	1784.9	1850.1	1866.4	3064.0	3059.7	2061.7	2061.8	1312.7	1313.3

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9. Elasticity estimation by income group – rural context.

Variable	1st income group		2nd income group		3rd income group		4th income group		5th income group		6th income group	
	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4
log (fuel cost)	0.130		-0.501 *		-0.217		-0.135		-0.535 ***		0.101	
	0.361		0.245		0.144		0.094		0.135		0.134	
log (time cost)	-0.510 ***		-1.351 ***		-1.456 ***		-1.394 ***		-1.296 ***		-1.839 ***	
	0.147		0.094		0.101		0.101		0.149		0.191	
log(time-inclusive cost)		-0.810 ***		-1.620 ***		-1.835 ***		-1.545 ***		-1.412 ***		-1.842 ***
		0.218		0.111		0.114		0.110		0.164		0.187
Intercept	7.271 ***	6.917 ***	5.611 ***	6.945 ***	7.153 ***	7.839 ***	7.979 ***	8.455 ***	7.416 ***	8.803 ***	9.850 ***	9.727 ***
	0.833	0.303	0.575	0.185	0.343	0.144	0.251	0.120	0.360	0.191	0.413	0.232
Household size			-0.309 ***	-0.319 ***	-0.106 *	-0.113 *						
			0.055	0.056	0.053	0.051						
Household trips	0.196 ***	0.182 ***	0.146 ***	0.147 ***	0.120 ***	0.120 ***	0.075 ***	0.074 ***	0.118 ***	0.115 ***	0.127 ***	0.127 ***
	0.037	0.035	0.020	0.020	0.013	0.013	0.010	0.010	0.015	0.015	0.017	0.017
Drivers in the household			0.487 ***	0.514 ***	0.241 **	0.219 *						
			0.112	0.113	0.090	0.087						
Vehicles in household							0.082 *	0.082 *	0.187 ***	0.200 ***		
							0.033	0.033	0.047	0.049		
Households in rural areas			0.161	0.130			0.208 ***	0.214 ***			0.297 **	0.276 **
			0.092	0.093			0.058	0.057			0.099	0.098
Workers in household	0.130		-0.501 *		-0.217		-0.135		-0.535 ***		0.101	
	0.31		0.245		0.144		0.094		0.135		0.134	
Observations	92	92	163	163	204	204	323	323	147	147	93	93
Adjusted R^2	0.317	0.335	0.671	0.665	0.614	0.638	0.514	0.516	0.557	0.522	0.662	0.66
AIC	275.1	271.6	465.8	467.9	526.3	512.1	905.4	903.3	365.1	375.2	239.9	239.5
BIC	287.7	281.7	490.5	489.6	549.5	532.0	931.8	925.9	383.0	390.2	255.1	252.2

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2 Comparative Insights into Travel Time Cost and Fuel Cost Impacts on VMT

This section examines the elasticity of VMT in response to changes in travel time and fuel costs, drawing comparisons between our findings based on the new 2022 survey data and those reported by Taiebat et al. (2019).

In the Taiebat et al. (2019) study, the estimated elasticity of VMT with respect to travel time cost is -0.4, indicating a relatively strong behavioral response to changes in travel time cost. The study also finds that high-income households exhibit greater elasticity with respect to travel time costs compared to lower-income groups. This suggests that wealthier households are more responsive to reductions in time cost, likely due to the higher value they place on their time.

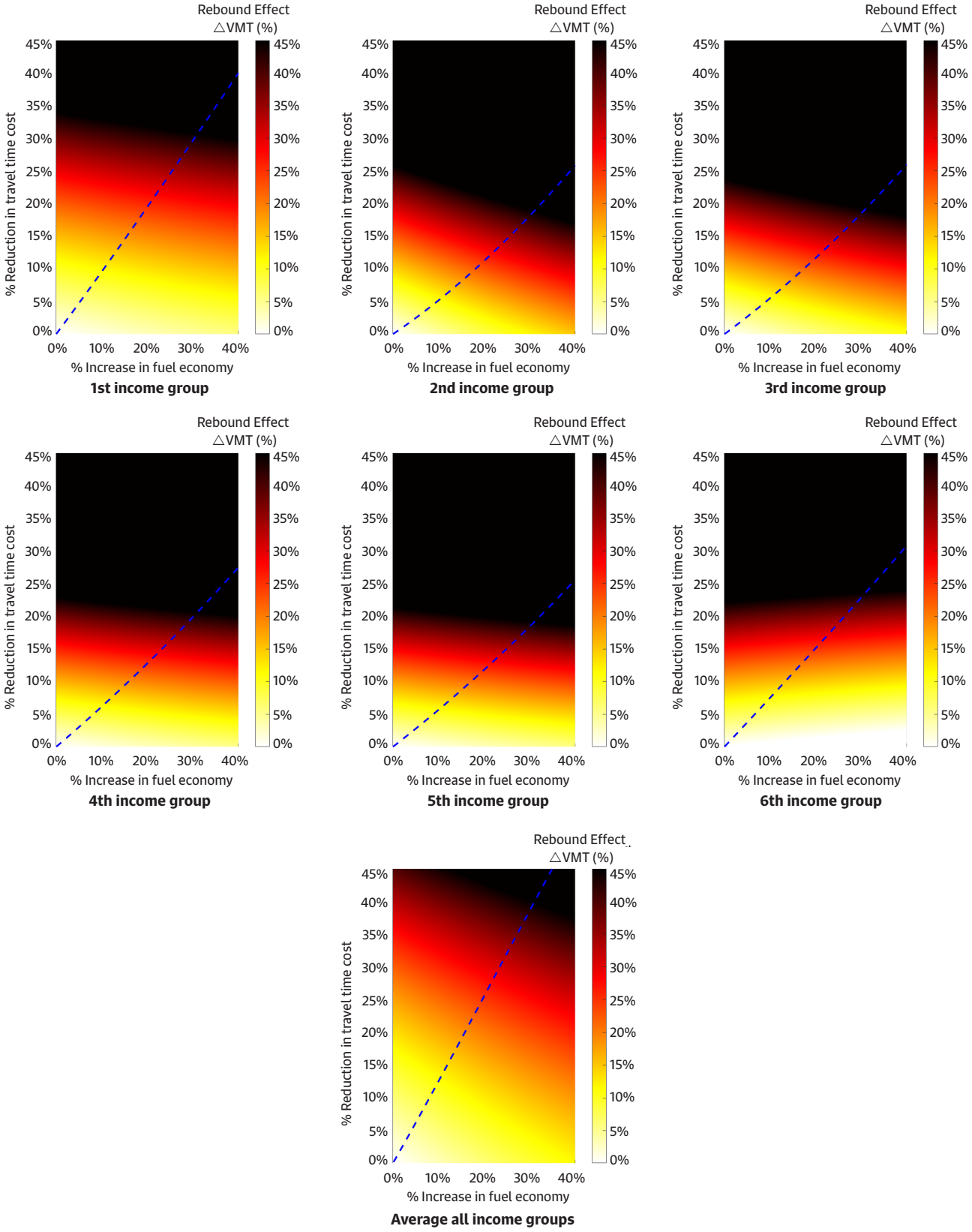
Our findings similarly underscore that high-income households exhibit greater elasticity with respect to travel time costs compared to lower-income groups. The study further reveals that rural households exhibit higher elasticity to travel time cost compared to urban households. This reflects the heightened value of time savings in urban settings, where congestion and higher opportunity costs make time reductions more impactful. Additionally, rural travelers rely more heavily on personal vehicles, making them more responsive to time cost changes. Our analysis estimates higher elasticity values than those reported by Taiebat et al. (2019), with travel time cost elasticity around -0.565 in general contexts. The greater elasticity in our findings (-0.565) compared to Taiebat et al. (2019) (-0.4486) is likely due to the use of updated data (2022 vs. 2016). This difference is supported by changes in average income levels: Taiebat et al. (2019) reported an average income of $70,237, whereas our analysis, based on the most recent dataset, indicates an average income of $103,303.

Regarding fuel cost, the elasticity of VMT with respect to fuel cost is -0.0989 in the Taiebat et al. (2019) study, indicating a lower sensitivity compared to time cost. Our findings align, showing that fuel cost reductions contribute to increased VMT, but the effect is less pronounced compared to time cost reductions. Our analysis estimates elasticity values that are higher than those of Taiebat et al. (2019), with fuel cost elasticity around -0.337 in general contexts. The higher fuel cost elasticity (-0.337) in our findings compared to Taiebat et al. (2019) (-0.0989) likely results from updated data (2022 versus 2017). Fuel cost and economic conditions changed between these periods, likely affecting how travelers responded to fuel cost variations. For example, households facing higher fuel prices in 2022 might have adjusted their travel more significantly compared to 2017.

4.3 Simulation: Travel and Energy Rebounds of CAVs

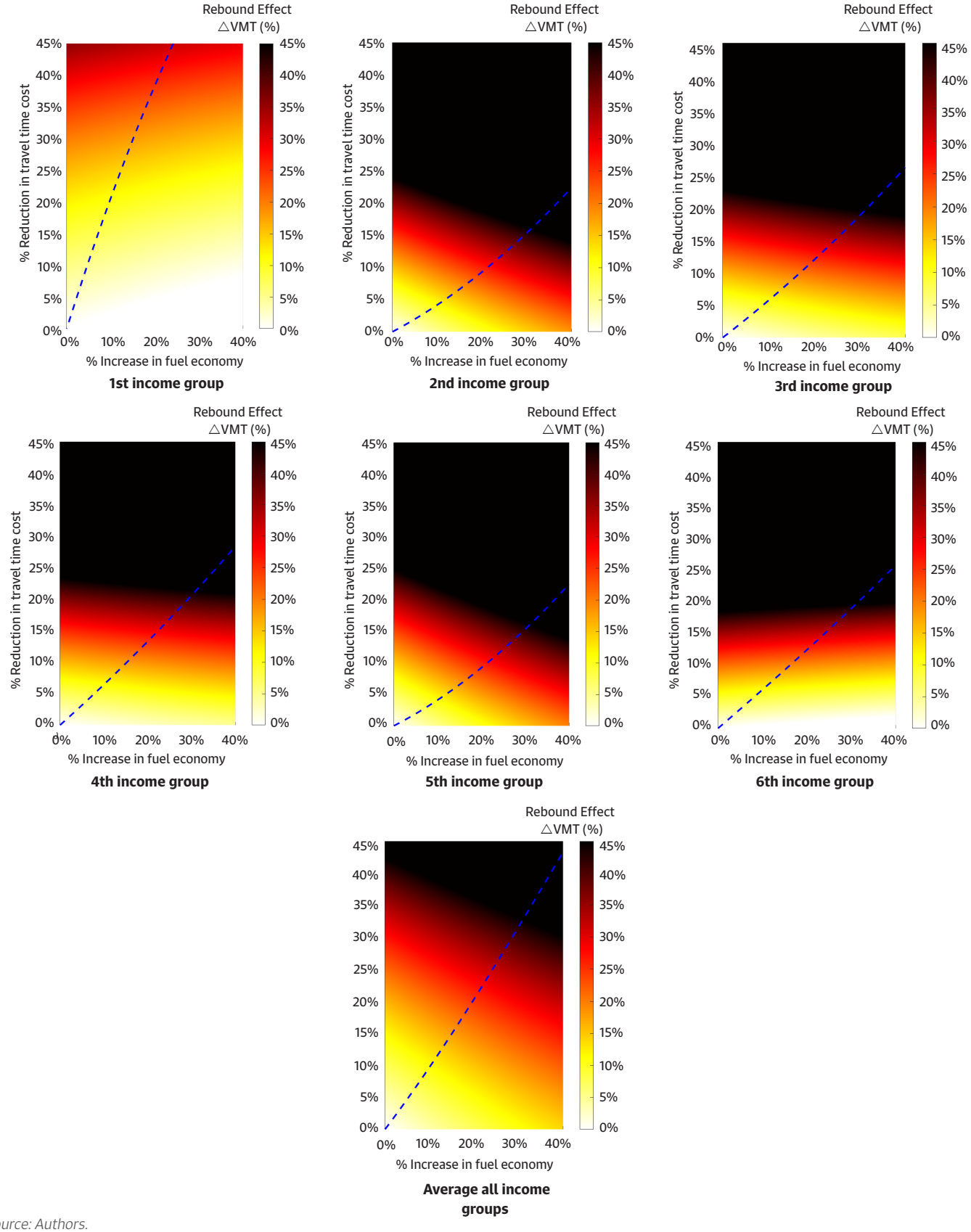
Figure 3 and Figure 4 illustrate the rebound effect of CAVs on VMT in urban and rural settings across different income groups. The X-axis represents the percentage increase in fuel economy, while the Y-axis shows the percentage reduction in travel time cost. The heatmaps depict the rebound effect in VMT as a percentage, with darker colors (red to black) indicating higher rebound effects.

Figure 3. Rebound effect of CAVs on VMT – urban.



Source: Authors.

Figure 4. Rebound effect of CAVs on VMT – rural.



Source: Authors.

A key observation across all scenarios is the positive rebound effect, where improvements in fuel economy and reductions in travel time costs lead to an increase in VMT. As fuel economy improves (moving rightward on the X-axis) and travel time costs decrease (upward on the Y-axis), the rebound effect becomes more pronounced, as indicated by the darker regions on the heatmaps (shades of red to black).

The comparison between rural and urban areas highlights distinct patterns in the rebound effect of VMT based on fuel economy improvements and reductions in travel time costs. In rural areas, the rebound effect (average of all income groups) is significantly more pronounced, as indicated by the darker regions on the heatmap. This can be attributed to the longer travel distances typically required in rural settings, where fuel economy improvements lead to substantial cost savings per mile. Additionally, rural residents often rely heavily on personal vehicles due to limited alternative transportation options, which amplifies the impact of reduced travel costs, even with small increases in fuel economy. For instance, a study by Ahmadnia and Rowangould (2024) analyzed data from 132,141 households in Vermont and found that a 10% increase in fuel efficiency led to a 1.4% increase in miles driven, a 14% rebound effect. This effect was more pronounced in rural areas, where people are more automobile-dependent and drive longer distances. The rebound effect in rural areas is noticeable and grows more significant as travel time cost reductions increase. This suggests that rural drivers are particularly sensitive to both factors, likely because of the essential nature of their trips and the relative lack of congestion.

In contrast, the rebound effect in urban areas is less pronounced, as evidenced by the lighter regions in the corresponding heatmap. Urban drivers tend to have shorter trip distances and greater access to alternative transportation options such as public transit, walking, or biking. These factors reduce their dependency on personal vehicles and limit the extent to which cost reductions translate into increased VMT. Even at similar levels of fuel economy improvements or travel time cost reductions, the urban rebound effect remains moderate. Congestion in urban areas further dampens the potential for induced travel, as time savings from reduced travel costs are often offset by traffic conditions (Litman 2023).

Income levels play a significant role in influencing the rebound effect. Higher-income groups demonstrate a more pronounced rebound effect, as indicated by the darker regions on the heatmaps, even at moderate improvements in fuel economy and reductions in travel time costs. For these groups, the value of time savings is particularly significant, making them more responsive to changes in travel costs. While higher-income individuals may not be as constrained by fuel expenses, reductions in travel time costs can incentivize additional travel, leading to a notable increase in VMT. This suggests that, for higher-income groups, the rebound effect is driven primarily by time-related efficiencies rather than direct fuel cost savings, as shown in Table 8 and Table 9.

The implications of this rebound effect are significant, particularly for energy efficiency and emissions reduction policies. The increase in VMT due to the rebound effect offsets the expected energy savings from fuel economy improvements, especially in rural areas. This presents a critical challenge for policymakers aiming to reduce transportation emissions. In urban areas, strategies such as congestion pricing or road tolls can be effective in counteracting the rebound effect by reducing the financial incentive to increase travel. In rural areas, policies could focus on reducing dependency on private vehicles by promoting public transportation or improving rural transit options.

The role of connected vehicles in improving travel efficiency and reducing costs underscores the need for complementary measures. Promoting alternative transportation modes, implementing better land-use planning, and managing induced travel demand are crucial to ensuring that the benefits of connected vehicles do not come at the expense of increased emissions and energy consumption.

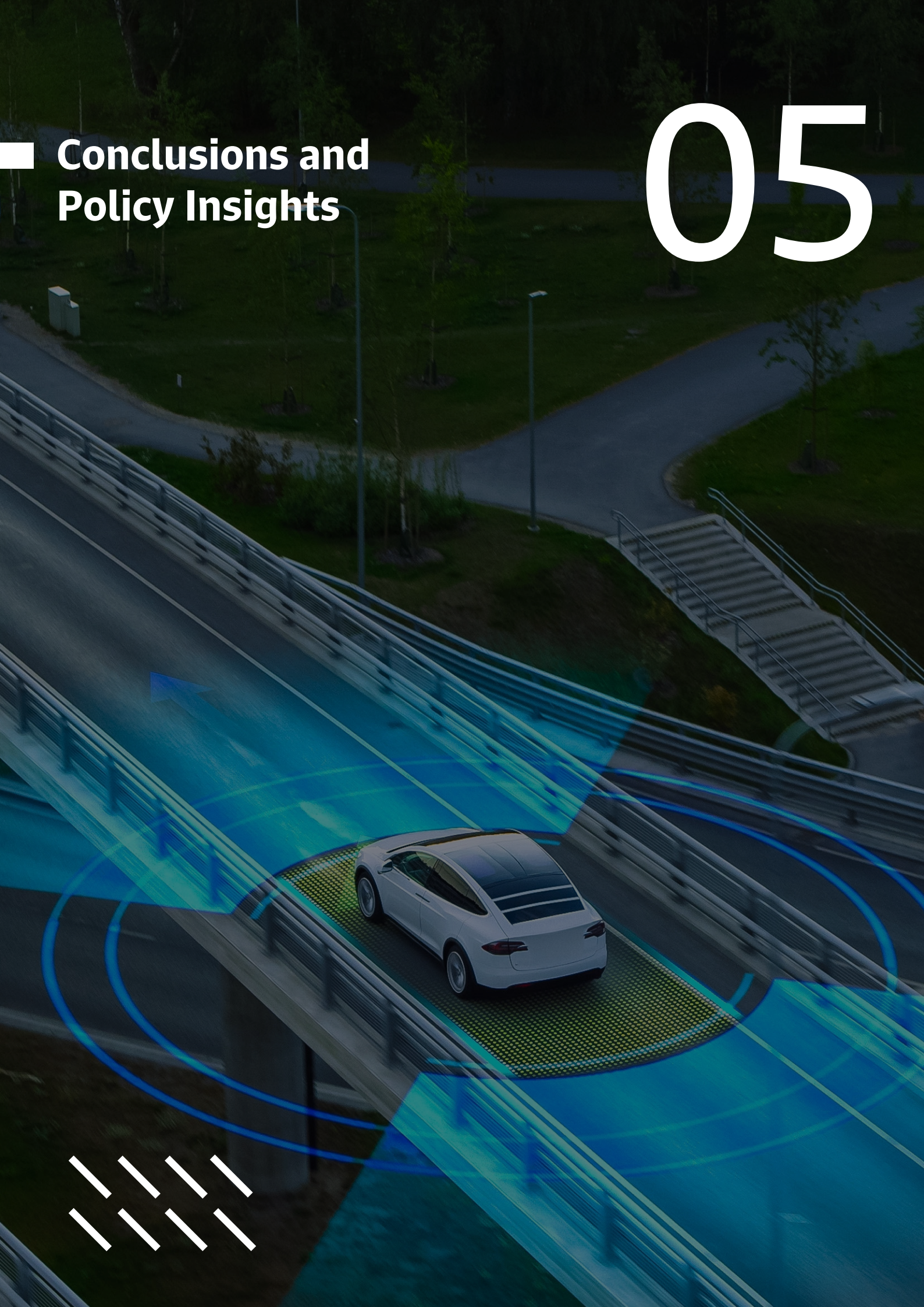
Table 10 summarizes the rebound effects of energy efficiency improvements or travel cost reductions in both urban and rural areas, detailing three key aspects: Initial Rebound Effect, Sensitivity to Parameters, and Policy Focus.

Table 10. Rebound effects of energy savings in urban and rural areas.

Aspect	Urban	Rural
Initial Rebound Effect	Lower, due to congestion and shorter trip distances.	Higher, as rural trips are longer, and cost reductions have a greater impact.
Sensitivity to Parameters	Significant rebound only at high fuel economy improvements and travel cost reductions.	Rebound effect noticeable even at moderate changes.
Policy Focus	Congestion pricing, road tolls, and alternative modes of transport.	Road tolls, public transport incentives to reduce private vehicle dependency.

05

Conclusions and Policy Insights



Conclusions and Policy Insights

This study provides a critical examination of the impact of CAVs on travel demand, fuel efficiency, and time costs, with a particular focus on urban versus rural settings.

By applying econometric models to household-level data from the 2022 National Household Travel Survey (NHTS), the analysis uncovers essential insights into the behavioral shifts induced by CAV technology, shedding light on the complexities of the energy rebound effect.

Key findings reveal that time cost elasticity is significantly higher than fuel cost elasticity, indicating that reductions in perceived travel time – enabled by CAVs – will be the primary driver of induced travel. In the preferred linear model, the time cost elasticity of VMT is -0.565 for the general population, -0.558 in urban areas, and -0.672 in rural areas, suggesting that rural households are more responsive to changes in time-related travel costs due to their longer travel distances and lack of modal alternatives.

Fuel cost elasticity, while lower, remains substantial. The general sample shows a fuel cost elasticity of -0.337, with rural areas displaying the highest sensitivity (-0.386) compared to urban areas (-0.323). These findings highlight that both components – fuel and time – must be considered in energy rebound assessments.

Moreover, the income-stratified analysis reveals substantial heterogeneity in behavioral response. For the lowest-income group, time cost elasticity is -0.835, indicating a moderate but meaningful sensitivity to travel time reductions. In contrast, the highest-income group exhibits a markedly higher elasticity of -1.504, suggesting that wealthier households are significantly more responsive to time cost savings and thus more susceptible to the energy rebound effect.

These elasticity estimates are further reinforced by the simulation analysis, which models improvements in fuel efficiency (0%-40%) and reductions in time costs (0%-45%). Results show consistently positive rebound effects across all scenarios, with rural areas experiencing the most pronounced VMT increases. The heatmap analysis confirms that rural households are more elastic with respect to time cost reductions than their urban counterparts – reflecting their greater dependence on personal vehicles and limited access to alternative modes of transport.

From a policy perspective, these findings emphasize the importance of proactive strategies to mitigate potential unintended consequences of widespread CAV deployment. Policymakers and urban planners should consider mechanisms such as congestion pricing, demand management strategies, and incentives for shared mobility solutions to ensure that CAVs contribute to energy savings and sustainable mobility rather than exacerbating VMT and emissions.

Additionally, the implications of this study extend beyond the U.S., offering valuable insights for regions like Saudi Arabia, where energy and transportation policies are rapidly evolving in response to emerging mobility technologies. Future research can explore how policy instruments – such as congestion pricing, VMT-based taxation, and shared mobility incentives – can be optimized to mitigate rebound effects while promoting sustainable, inclusive, and energy-efficient transport systems.

Endnote

[1] SAE International defines vehicle automation across six levels (0-5). Level 3 (“Conditional Automation”) allows the vehicle to perform all driving tasks in specific scenarios without driver input; however the driver must remain available to take over. Level 4 (“High Automation”) enables full driving without human intervention, but only within limited operational domains (e.g., geofenced urban areas).

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Appendix

Table A1. Elasticity estimation by income group – general context.

Variable	1st income group		2nd income group		3rd income group		4th income group		5th income group		6th income group	
	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4
log (fuel cost)	-0.177		-0.430 ***		-0.285 ***		0.416 *		-0.233 ***		0.110	
	0.127		0.067		0.066		0.205		0.061		0.067	
(log (fuel cost))^2							0.099 **					
							0.034					
log (time cost)	-1.312 ***		-1.280 ***		-1.376 ***		-1.374 ***		-1.504 ***		-1.848 ***	
	0.141		0.042		0.039		0.041		0.046		0.153	
(log (time cost))^2	-0.171 ***				0.044		-0.077 *				0.139 *	
	0.046				0.025		0.034				0.058	
log(time-inclusive cost)		-1.495 ***		-1.510 ***		-1.657 ***		-1.552 ***		-1.755 ***		-1.968 ***
		0.154		0.055		0.047		0.053		0.113		0.169
(log(time-inclusive cost))^2		-0.145		0.195 ***		0.150 ***		-0.018		0.091		0.159 **
		0.088		0.057		0.032		0.041		0.063		0.061
Intercept	6.015 ***	6.584 ***	5.829 ***	6.865 ***	7.022 ***	7.817 ***	8.631 ***	8.380 ***	8.701 ***	9.425 ***	10.143 ***	10.091 ***
	0.294	0.153	0.159	0.080	0.153	0.063	0.294	0.064	0.159	0.085	0.190	0.127
Household size			-0.086 ***	-0.095 ***	-0.079 ***	-0.080 ***	-0.054 **	-0.046 *	-0.054 *	-0.055 *		
			0.025	0.025	0.022	0.022	0.021	0.021	0.022	0.023		
Household trips	0.113 ***	0.111 ***	0.130 ***	0.131 ***	0.138 ***	0.138 ***	0.096 ***	0.096 ***	0.087 ***	0.088 ***	0.113 ***	0.111 ***
	0.012	0.012	0.009	0.009	0.008	0.008	0.005	0.005	0.006	0.006	0.007	0.007

Table A1. Continued

Variable	1st income group		2nd income group		3rd income group		4th income group		5th income group		6th income group	
	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4
Drivers in the household			0.117 *	0.131 *			0.154 ***	0.137 ***				
			0.052	0.053			0.042	0.042				
Vehicles in household			0.094 **	0.092 *	0.065 **	0.063 **	0.045 *	0.051 *	0.076 **	0.072 **		
			0.036	0.037	0.023	0.023	0.023	0.023	0.024	0.024		
Households in urban/rural areas	-0.218	-0.210										
	0.114	0.114										
Workers in household	0.102	0.097	0.184 ***	0.195 ***	0.183 ***	0.185 ***	0.136 ***	0.139 ***	0.158 ***	0.160 ***	0.154 ***	0.152 ***
	0.062	0.062	0.038	0.038	0.033	0.033	0.026	0.026	0.031	0.031	0.039	0.039
Observations	363	363	830	830	903	903	1489	1489	943	943	587	587
Adjusted R^2	0.503	0.502	0.63	0.62	0.666	0.668	0.637	0.634	0.621	0.617	0.642	0.639
AIC	1063.1	1062.7	2213.2	2234.3	2344.6	2339.5	3914.3	3926.7	2397.7	2406.7	1521.3	1525.1
BIC	1094.3	1090.0	830	830	2387.9	2377.9	3972.7	3974.5	2436.5	2445.5	1551.9	1551.3

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2. Elasticity estimation by income group urban context.

Variable	1st income group		2nd income group		3rd income group		4th income group		5th income group		6th income group	
	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4
log (fuel cost)	-0.145		-0.416 ***		-0.291 ***		0.324		-0.161 *		0.113	
	0.135		0.066		0.071		0.216		0.065		0.077	
$(\log(\text{fuel cost}))^2$							0.090 *					
							0.039					
log (time cost)	-1.284 ***		-1.240 ***		-1.407 ***		-1.382 ***		-1.546 ***		-1.808 ***	
	0.151		0.048		0.045		0.047		0.050		0.171	
$(\log(\text{time cost}))^2$	-0.152 **				0.105 ***		-0.066				0.124 *	
	0.050				0.030		0.036				0.062	
log (time-inclusive cost)		-1.367 ***		-1.514 ***		-1.717 ***		-1.588 ***		-1.904 ***		-2.010 ***
		0.097		0.061		0.058		0.042		0.133		0.195
$(\log(\text{time-inclusive cost}))^2$				0.208 **		0.182 ***				0.142 *		0.166 *
				0.065		0.036				0.072		0.067
Intercept	5.888 ***	6.438 ***	5.977 ***	6.951 ***	6.969 ***	7.789 ***	8.494 ***	8.427 ***	8.989 ***	9.574 ***	10.192 ***	10.223 ***
	0.269	0.137	0.147	0.078	0.156	0.070	0.284	0.067	0.162	0.093	0.200	0.151
Household size	-0.097 *	-0.075			-0.091 ***	-0.087 ***	-0.055 *	-0.048 *	-0.050 *	-0.065 *		
	0.042	0.042			0.025	0.025	0.024	0.024	0.024	0.027		
Household trips	0.117 ***	0.113 ***	0.122 ***	0.123 ***	0.148 ***	0.146 ***	0.102 ***	0.104 ***	0.082 ***	0.084 ***	0.110 ***	0.107 ***
	0.014	0.014	0.010	0.010	0.010	0.010	0.006	0.006	0.006	0.006	0.008	0.008

Table A2. Continued

Variable	1st income group		2nd income group		3rd income group		4th income group		5th income group		6th income group	
	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4
Drivers in the household	0.181 *	0.146					0.186 ***	0.173 ***		0.083		
	0.085	0.083					0.042	0.042		0.046		
Vehicles in household			0.093 **	0.095 **	0.053	0.050			0.049			
			0.035	0.036	0.027	0.027			0.027			
Households in urban areas			0.169 ***	0.177 ***	0.248 ***	0.253 ***	0.121 ***	0.124 ***	0.173 ***	0.159 ***	0.127 **	0.130 **
			0.039	0.039	0.039	0.039	0.029	0.029	0.033	0.036	0.042	0.043
Workers in household	-0.145		-0.416 ***		-0.291 ***		0.324		-0.161 *		0.113	
	0.135		0.066		0.071		0.216		0.065		0.077	
Observations	271	271	667	667	699	699	1166	1166	796	796	494	494
Adjusted R^2	0.535	0.527	0.616	0.605	0.668	0.664	0.646	0.644	0.628	0.626	0.636	0.634
AIC	790.8	793.3	1730.6	1749.7	1803.5	1811.6	3018.8	3024.3	2024.3	2027.1	1285.4	1288.2
BIC	819.6	814.9	1762.1	1781.2	1844.4	1848.0	3069.4	3059.7	2061.7	2064.6	1314.8	1313.4

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3. Elasticity estimation by income group – rural context.

Variable	1st Income Group		2nd Income Group		3rd Income Group		4th Income Group		5th Income Group		6th Income Group	
	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4
log (fuel cost)	-3.990		7.065 **		-0.242		0.588		-0.535 ***		-1.529 *	
	2.953		2.216		0.138		0.454		0.135		0.762	
(log (fuel cost))^2	-0.863		1.545 ***				0.112				-0.239 *	
	0.607		0.450				0.066				0.110	
log (time cost)	-1.352 ***		-1.342 ***		-1.897 ***		-1.368 ***		-1.296 ***		-1.904 ***	
	0.398		0.091		0.145		0.102		0.149		0.189	
(log (time cost))2	-0.263 *				-0.275 ***		-0.208					
	0.115				0.067		0.118					
log(time-inclusive cost)		-1.385 **		-1.620 ***		-2.029 ***		-1.545 ***		-1.412 ***		-1.842 ***
		0.442		0.111		0.147		0.110		0.164		0.187
(log(time-inclusive cost))2		-0.307				-0.232 *						
		0.205				0.113						
Intercept	1.850	6.746 ***	14.819 ***	6.945 ***	7.135 ***	7.895 ***	8.956 ***	8.455 ***	7.416 ***	8.803 ***	7.471 ***	9.727 ***
	3.615	0.322	2.738	0.185	0.330	0.146	0.725	0.120	0.360	0.191	1.168	0.232
Household size			-0.292 ***	-0.319 ***	-0.114 *	-0.115 *	-0.067					
			0.054	0.056	0.051	0.051	0.045					
Household trips	0.205 ***	0.181 ***	0.140 ***	0.147 ***	0.120 ***	0.120 ***	0.078 ***	0.074 ***	0.118 ***	0.115 ***	0.121 ***	0.127 ***
	0.038	0.035	0.019	0.020	0.013	0.013	0.010	0.010	0.015	0.015	0.017	0.017
Drivers in the household			0.404 ***	0.514 ***	0.195 *	0.198 *	0.164					
			0.111	0.113	0.088	0.087	0.100					

Table A3. Continued

Variable	1st Income Group		2nd Income Group		3rd Income Group		4th Income Group		5th Income Group		6th Income Group	
	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4
Vehicles in household							0.066	0.082 *	0.187 ***	0.200 ***		
							0.034	0.033	0.047	0.049		
Households in rural areas			0.220 *	0.130			0.216 ***	0.214 ***			0.295 **	0.276 **
			0.091	0.093			0.063	0.057			0.097	0.098
Workers in household	-3.990		7.065 **		-0.242		0.588		-0.535 ***		-1.529 *	
	2.953		2.216		0.138		0.454		0.135		0.762	
Observations	92	92	163	163	204	204	323	323	147	147	93	93
Adjusted R^2	0.356	0.344	0.693	0.665	0.642	0.644	0.521	0.516	0.557	0.522	0.676	0.66
AIC	271.6	271.3	455.8	467.9	511.7	509.7	904.5	903.3	365.1	375.2	237.0	239.5
BIC	289.3	283.9	483.7	489.6	538.3	533.0	946.0	925.9	383.0	390.2	254.7	252.2

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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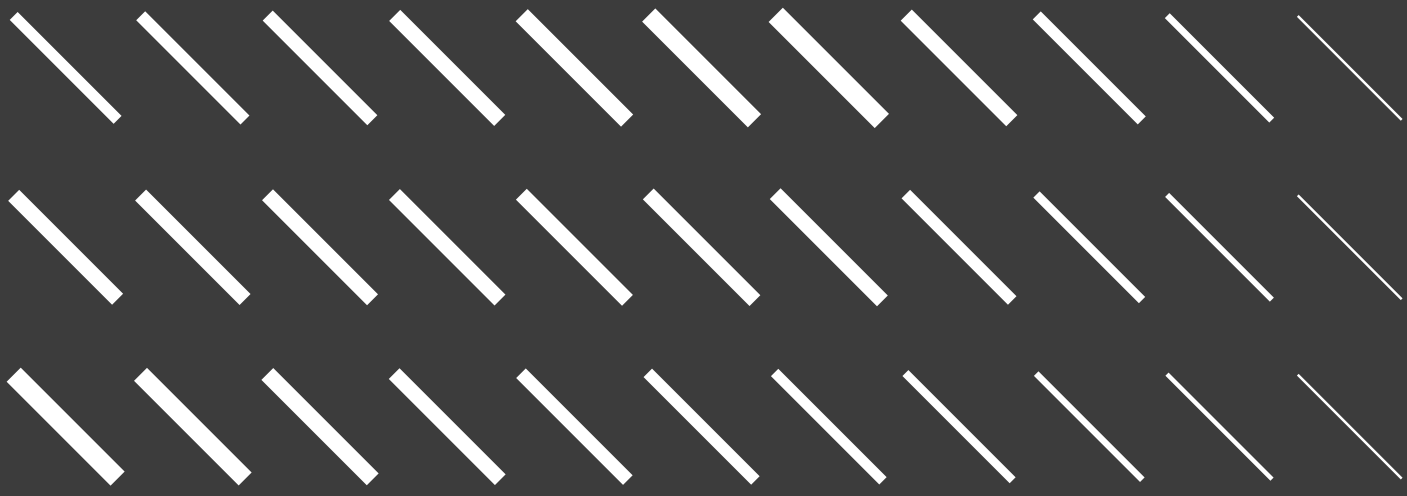
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About the Project

The project “An Integrated Transport Energy Demand Model for KSA” aims to develop a comprehensive framework covering all transport sectors at both national and urban levels, while also incorporating cross-border interactions with neighboring countries. As a decision-support tool, it will enable policymakers and stakeholders to evaluate the impacts of policy measures, infrastructure developments, and decarbonization strategies on the transport sector.





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