

Uncovering the determinants of bottom-up CO₂ emissions among households in Türkiye: Analysis and policy recommendations

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ARTICLE INFO

Handling Editor: Giovanni Baiocchi

Keywords:

Censored regression
Double-hurdle
Households
Private fuel spending
Türkiye

ABSTRACT

Amid escalating global concerns surrounding climate change, the transportation sector has garnered the attention of stakeholders. Double-hurdle censored models were employed in this study to elucidate the relationship between the probability of private fuel expenditure and expenditure levels and household characteristics to determine the factors contributing to household-based CO₂ emissions. Remarkably, nearly two-thirds of the 38 factors examined contributed to the emitters, and almost all emitters were identified as statistically significant. This alarming situation underscores the importance of formulating family based green transformation policies. If successful, these policies can ignite transformative momentum. Consequently, understanding household transportation expenditure from a bottom-up perspective can provide invaluable insights into crafting a comprehensive set of top-line policy recommendations for innovation and marketing strategies in the transport and energy sectors. Measures such as incentivizing the adoption of electric vehicles through economic incentives, expanding public transportation networks, and implementing sustainable housing policies have immense potential to effectively reduce private fuel expenditure. When implemented holistically, these strategies can pave the way for a more sustainable and environmentally friendly future.

1. Introduction

The pursuit of green transformation and sustainable transportation is crucial for combating the impacts of climate change, reflecting a dedicated commitment to forging a sustainable future by mitigating carbon footprints (OECD, 2021). Nations are not solely focused on economic advancement but are equally dedicated to nurturing environmentally friendly growth (Bayat et al., 2023) and actively addressing the substantial challenge of high carbon emissions (Hao et al., 2014; Bayat et al., 2023). As a signatory to the United Nations Framework Convention on Climate Change and Kyoto Protocol, Türkiye is steadfast in fulfilling its international obligations in the battle against global warming (MFA, 2023). The G20 economic coalition plays a pivotal role, representing approximately 85% of the global gross domestic product (GDP) and over 50% of the world's population. The G20 economies, including Türkiye, are responsible for 70% of the global climate impact (Habib

et al., 2021). Consequently, G20 member states have initiated green initiatives to mitigate environmental risks stemming from economic activities (Ali et al., 2024; Sheraz et al., 2021; OECD, 2021).

The complex relationship between transportation activities and economic factors has drawn increased attention from policymakers owing to its mounting environmental ramifications and has demanded rigorous action (Sharif et al., 2019; Habib et al., 2021). One of the cornerstone elements of transportation modalities revolves around road transportation, encompassing personal and commercial vehicles such as cars, trucks, buses, and motorcycles. The fuel consumption and exhaust emissions from these vehicles constitute integral facets of road transport (Andrés and Padilla, 2018; Solaymani, 2019; IEA, 2019a; Habib et al., 2021). Without effective mitigation strategies, global CO₂ emissions from the transport sector are projected to increase by approximately 60% by 2050 (ITF, 2019). Despite the adoption of decarbonized transport systems, global CO₂ emissions are expected to increase by < 16% by 2050, posing a

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significant challenge (M.M. Hussain et al., 2023; Habib et al., 2021). Because road transport accounts for a substantial share of global oil consumption, it is imperative to achieve a net-zero emissions target for the transport sector (IEA, 2019b; Dai et al., 2023). Moreover, the unification of economic growth, urbanization, and rising income has fueled an upsurge in transportation demand, thereby expanding the environmental footprint (Habib et al., 2021; Hussain Z et al., 2023; Dai et al., 2023). Projections indicate that, by 2050, global passenger numbers will double from 2010 to nearly 2.4 billion millennials, underscoring the urgency of addressing this challenge (Habib et al., 2021). Despite a temporary 12% decline in CO₂ levels in 2020 due to the global COVID-19 pandemic, projections anticipate a recovery and increase in emissions from transportation in the coming years (STATISTA, 2022).

Although developed countries have diversified and clean energy structures (Huang and Matsumoto, 2021), the energy consumption of Türkiye is highly dependent on high-carbon fuels. Türkiye's rapid growth in energy consumption and greenhouse gas (GHG) emissions has raised concerns among governments (Bayat et al., 2023). Türkiye's transport sector has developed rapidly, creating a series of environmental problems, including energy consumption and CO₂ emissions. Although emission intensity and fuel switching trends in the transportation sector were promising from 2000 to 2010, the surge in the popularity of sports utility vehicles in recent years posed challenges to emission reduction efforts between 2010 and 2017 (Isik et al., 2020). In the first half of 2023, the number of registered vehicles in Türkiye surged by a remarkable 81.9% compared to the same period in the previous year, reaching a total of 1 million 57 thousand 643. The transition to sustainability is also evident in sales figures. In 2023, 197,379 hybrids and 51,219 electric vehicles were sold in the country compared to 83 hybrids and 353 electric vehicles in 2013. The adoption rate of hybrids and electric vehicles has increased to 1.6% in the last decade, which is a noteworthy increase (TSI and Turkish Statistical Institute, 2023). A significant milestone was achieved in October 2023 when electric vehicle sales surpassed diesel sales for the first time (ODMD, 2023).

Household consumption accounts for approximately 60% of global GHG emissions worldwide (Ivanova et al., 2016; Wiedenhofer et al., 2018); even in China, a country boasting a colossal economy, the share of household consumption in GHG emissions is 30% (Xie et al., 2023). In this context, understanding the behavioral characteristics of households is indispensable for controlling household-related GHG emissions for policymakers and sectoral stakeholders (Xie et al., 2023). This is because the policy aspects regulating households' options, the efficient use of fossil fuels, and the abilities of household members to curb such fossil fuel use vary. Additionally, thoroughly scrutinizing household carbon emissions and steering households towards low-carbon consumption patterns are of paramount importance (Cao et al., 2019). It is also imperative to examine whether non-income-related household behavioral variations are associated with emissions, because this could impact the distributional effects of mitigation policies (Büchs and Schnepf, 2013). Given Türkiye's significant share of fossil fuel consumption, uncovering the determinants of CO₂ emissions at the household level empirically is crucial. Therefore, the primary objective of this study is to statistically establish a causal relationship between households' average monthly expenditure on fossil fuels (diesel, gasoline, and Liquefied Petroleum Gas [LPG]) for private cars and varying behavioral factors at the household level. In particular, to diminish the amount of CO₂ contributing to climate change at the household level, the findings of the current study aim to inform policymakers about the effectiveness of implemented policy measures, which are determined by household behavioral characteristics at the basic level. This study employs an error-dependent double-hurdle (DH) censored econometric model to assess the relationship between household's monthly fossil fuel expenditure for private passenger cars and their sociodemographic and economic behavioral factors. Furthermore, the interactions among key behavioral characteristics, such as the household head's educational level, household income group, and cohort level, on the probability and

conditional and unconditional levels of fossil fuel expenditure were empirically demonstrated. The absence of such an interaction was statistically tested using a null hypothesis analysis. Additionally, the hypothesis of a shift towards more sophisticated energy carriers by households with increasing income levels, known as the energy ladder, was tested in this study. Although this study is specific to Türkiye, we hope that it sheds light on the bottom-up energy policy formulation process for other countries with similar characteristics and provides an internationally applicable perspective on reducing CO₂ emissions.

2. Literature review

A noteworthy portion of carbon emissions stem from household activities (Li et al., 2015). Nearly 80% of the household emissions originate from transportation, residences, fuel types (Alajmi, 2021), and food preferences (Christis et al., 2019; Pichler et al., 2017). Since 2002, there has been a steady increase in the consumption patterns of services, housing, food, and transportation in rural and urban areas (Wang et al., 2019). Household carbon footprints are complexly linked to energy consumption and individual circumstances, showing varying impacts across provinces and urban-rural divides (Ata et al., 2023). Understanding lifestyle shifts or behavioral changes is pivotal to effective urban planning policies (Apergis and Li, 2016). Notably, urbanization in developing nations is expected to catalyze changes in consumption behavior, favoring an increased reliance on motorized transport and electronic devices (Apergis and Li, 2016). As shown by Zhu et al. (2017), urbanization accounts for 74.1% of household emissions. Technological advancements alone cannot fully offset escalating emissions resulting from population growth and rising prosperity (Feng et al., 2009).

Regarding energy consumption and CO₂ emissions, the transportation sector is the fastest growing sector worldwide (Ma et al., 2015; Wang et al., 2019), making consumption trends increasingly pivotal for determining CO₂ emission levels (Huang and Matsumoto, 2021; Wang et al., 2019). To steer households towards low-carbon consumption behaviors, a comprehensive assessment of household carbon footprints has emerged worldwide as a potent strategy for mitigation purposes (Cao et al., 2019; Xie et al., 2023). Consequently, adjustments in household transportation practices have emerged as a primary avenue of action when crafting behavior-change policies (Ding et al., 2017; Ivanova et al., 2020; Moran et al., 2020). Numerous studies have explored household emission disparities using decomposition analyses (Das and Paul, 2014; Gill and Moeller, 2018; Guan et al., 2014; Wang and Liu, 2014). Cao et al. (2019) scrutinized the factors influencing Chinese household carbon emissions using the log mean Divisia index model, whereas Yang et al. (2015) investigated the nexus between China's transportation-related CO₂ emissions and urban infrastructure development by employing a two-way fixed-effect model. Socioeconomic progress and income upsurges have predominantly contributed to per capita CO₂ emissions from transportation (Yang et al., 2015). Their findings revealed that a 1% expansion in urban built-up areas translated into a 0.08% increase in transportation-related CO₂ emissions per capita. Moreover, they noted that a 1% increase in urban population density and urban road density corresponds to 0.22% and 0.16% increases in CO₂ emissions per capita, respectively. Income levels also significantly shape emissions patterns at the household level (Christis et al., 2019). Household emissions are also influenced by income disparities, divergences in energy utilization, dietary preferences, and access to communal amenities (Dou et al., 2021; Zhang et al., 2020). The profound impacts of lifestyle choices (Apergis and Li, 2016) and consumption habits on CO₂ emissions have been widely acknowledged (Wang et al., 2019).

Li et al. (2015) and Wang et al. (2019) employed a factor-reversible structural decomposition method coupled with an input-output analysis to thoroughly study the implications of urbanization and consumption trends on household contributions to carbon emissions. Conversely, the context of household consumption has been a focal point in numerous

input-output model investigations (Das and Paul, 2014). By employing an input-output analysis, Das and Paul (2014) elucidated that household fuel consumption is chiefly influenced by activity, structure, and demographic factors. In a pivotal decomposition analysis, Andreoni and Galmarini (2016) underscored the paramount importance of enhancing energy efficiency in curbing CO₂ emissions. Bai et al. (2019) researched the relationship between socioeconomic factors and CO₂ emissions in Thailand based on economic input-output tables. According to Bai et al. (2019), education positively affects the requirements for direct energy and CO₂; however, it negatively impacts the consumption of secondary energy and CO₂. Utilizing the input-output methodology, Li et al. (2015) carefully calculated the direct and indirect CO₂ emissions emanating from Chinese households between 1996 and 2012, revealing that urban households surpassed their rural counterparts in total CO₂ emissions. Employing an extended stochastic regression model encompassing wealth, population, and technology, Miao et al. (2019) dissected the primary catalysts that drive household CO₂ emissions. The confluence of income, household size, and age intricately shapes individuals' decisions regarding household expenditure and CO₂ emissions. Soltani et al. (2020) found a robust correlation between household age, size, and CO₂ emissions, although there were no significant associations with household education or income. Thus, a holistic approach is warranted to determine the relative impact of each element on household CO₂ emissions (Ata et al., 2023; Soltani et al., 2020).

The household sector has emerged as a significant contributor to CO₂ emissions in Iran (Ata et al., 2023). Despite their prominence, existing policies have predominantly focused on large-scale endeavors, sidelining the pivotal role that households play in shaping and executing them. In Iran, households are the second largest emitter of CO₂ following transportation, accounting for 23.4% of total emissions (Ata et al., 2023). Notably, oil prices, energy subsidies, and educational attainment have emerged as key determinants of emissions, with GDP per capita exerting the most favorable influence on household CO₂ emissions. Moreover, household size and gas and oil consumption had significant positive impacts on CO₂ emissions. Yang et al. (2018) conducted a multiple regression analysis with individual carbon emissions as the dependent variable, and individual, household, and environmental characteristics as the independent variables. Access to public transport has emerged as a pivotal factor in mitigating emissions, with higher emissions being associated with male-gender, greater income, car ownership, and age between 30 and 40 years (Yang et al., 2018). Highlighting the predominant role of the transportation sector, the Energy Information Administration reports that it accounts for 36.7% of energy-related CO₂ emissions in the United States (EIA, Energy Information Administration, 2019). Conversely, Barla et al. (2011) conducted an illuminating longitudinal panel survey in the Quebec City region of Canada, demonstrating that transitioning to a 10% denser neighborhood could yield a 1.2% reduction in travel emissions. Diminishing bus travel duration was found to be particularly impactful in lowering GHG emissions, with a 10% reduction in commuting time potentially mitigating emissions by 2.7%. Legras and Cavailhès (2016) underscored commuters' substantial contribution to GHG emissions, whereas Zahabi et al. (2012) estimated household GHG emission inventories using disaggregated trip data and found that a 10% increase in public transportation accessibility was correlated with a 5.17% decrease in household GHG emissions.

Governments have considerable influence on steering societies towards energy-efficient and environmentally conscious transportation practices. Policymakers can actively encourage the adoption of low-carbon vehicles using a combination of financial incentives and strategic taxation, thereby curbing reliance on fossil fuels and mitigating harmful emissions from automobiles. Such measures alleviate environmental strain and pave the way for smarter urban management (Tian et al., 2020). Notably, congested traffic poses a significant environmental challenge as it emits far more CO₂ than vehicles operating at higher speeds. Tian et al. (2020) highlighted that addressing such an issue requires the implementation of Intelligent Transport Systems,

which can effectively alleviate congestion. Leveraging technologies such as Vehicle Information and Communication Systems further enhance fuel efficiency and lower emissions, thereby contributing to congestion alleviation. Moreover, the integration and enhancement of transportation infrastructure play a pivotal role in optimizing low-carbon technologies within urban landscapes, as reported by Tian et al. (2020). However, socioeconomic factors also exert a notable influence on emission trends. Büchs and Schnepf (2013) observed a correlation between rising income levels and increased emissions across all sectors. Interestingly, household composition and location also played a role in emission patterns. Rural households and those with children tend to exhibit higher emission levels than urban or childless households, as highlighted by Cao et al. (2019). Similarly, Büchs and Schnepf (2013) found that households with females or older reference persons were less likely to have high emissions. Another area of study concerns the complex relationship between education and emissions. Although Baiocchi et al. (2010) noted a negative correlation between having children and CO₂ emissions, they also found a positive correlation with education level. However, Brand and Preston (2010) found that university-educated individuals emit more transport-related emissions than non-educated individuals. Xie et al. (2023) analyzed household emissions in China and identified consumption expenditure as the primary driver of the differences between rural and urban households. This underscores the importance of understanding household consumption patterns when designing effective emission mitigation strategies. In the context of transportation, Xu and Lin (2015) argued for the use of non-linear models to better capture the complexities of economic variables and their impacts on CO₂ emissions. Similarly, Erdogan (2014) highlighted the inelastic nature of fuel demand in Türkiye, emphasizing the importance of nuanced policy interventions to foster sustainability in fuel markets. Robust strategies aimed at forecasting energy demand, assessing the ramifications of tax policies, and adapting to sectoral changes are essential for enhancing the resilience and sustainability of fuel markets, as suggested by Coruh and Bilgic (2023). As is evident from the extensive literature review, the intricate causal link between household behavioral traits and fossil fuel expenditure on private passenger cars remains obscure. This study aimed to illuminate this relationship by leveraging a comprehensive cross-sectional dataset enriched with diverse behavioral factors. Through meticulous analysis, we aim to unravel the underlying dynamics driving fossil fuel expenditure at the household level, elucidating the relationship between behavioral changes and energy consumption patterns.

3. Data and methods

3.1. Data

Data for this study were obtained from the most recent household budget survey administered to households throughout the country by the Turkish Statistical Institute (TSI) between January 1 and December 31, 2019.¹ The TSI aimed to purge seasonal effects on expenditures by replacing approximately 1000 families with the same characteristics every month. Disregarding certain missing observations, particularly qualitative variables, our study included 11,142 of the initial 11,541² family observations.

3.2. Econometric method

It is widely accepted that rational households seek to maximize their

¹ Because the first cases of COVID-19 in Türkiye were detected in February–March 2020, the analysis is free of this effect.

² Descriptive statistical explanations have been extensively discussed and detailed in the Findings section, directing the reader to that section for further elaboration.

utility, meaning they select the option that provides the highest utility among the alternatives available to them. In this context, various theories such as expected utility, prospect, random utility, and utility maximization theories have been proposed in the literature to explain decision-making involving choices or preferences across diverse fields ranging from tourism economics and transportation (Brida and Scuderi, 2013; Coruh et al., 2022; Downward and Lumsdon, 2000, 2003; Ma et al., 2019) to energy usage (Hanemann et al., 2024) and environmental quality (Saz-Salazar and Rausell-Koster, 2008) to economics and agricultural economics (Aksoy et al., 2019; Aristei and Pieroni, 2008; Bannor et al., 2022; Kahneman and Tversky, 1979). However, this study is grounded in random utility maximization theory, which posits that households are rational and exhibit consistent decisions with maximum satisfaction. Therefore, in this study, we assume that households, while considering the expected level of satisfaction, are willing to allocate a certain amount of money equivalent to the utility they would forgo from fossil fuel usage to ensure their well-being. In other words, households that use fossil fuels experience an increase in utility or well-being as a result of the benefits derived from using fossil fuels. Therefore, these households are willing to pay a certain amount to secure this gain in utility.³

Our empirical model, tailored for the double-hurdle censored regression where we will shortly define it below, operates under the context of discrete random utility theory, where households are guided by the pursuit of maximizing their utility function (Pudney, 1989) (observation subscripts are suppressed for brevity):

$$V(q, c, s) = dU(q, c; s) + (1 - d)U^*(c; s) \quad (1)$$

where U represents the utility derived from household fuel consumption and U^* stands for the utility derived from non-fuel uses. The variable q signifies monthly fuel consumption by households, where p denotes the unit price of fuel ($p > 0$). Furthermore, c denotes a composite quantity for other consumption goods, with the price normalized at unity, and s encapsulates a vector of household heads and demographic features catering to heterogeneous preferences (Coruh et al., 2022). The value $d \in (0,1)$ acts as a binary indicator, assuming a value of one under the following conditions: if the household engages in fuel consumption, and zero otherwise. In turn, the probit regression yields a binary outcome.

$$d = 1 \text{ if } z'\alpha + u > 0 \quad (2)$$

$$= 0 \text{ if } z'\alpha + u \leq 0$$

where z and α stand as vectors encapsulating variables and parameters, respectively, dictating participation, whereas u serves to capture random disturbances embodying unobserved characteristics. Given that

³ Yet another representation of direct utility maximization could be as follows: Let us weigh (i.e., differentiate) the perceived benefits (utility) of using fossil fuels ($U_{c,i}$) against those of opting out ($U_{nc,i}$), captured as G^* . Therefore, when the satisfaction derived from using fossil fuels outweighs that of abstaining ($G^* = U_{c,i} - U_{nc,i} > 0$), households—let us call them ‘i’—tend to lean towards fossil fuel consumption. Of course, households in this context incur specific costs related not directly to the fuel itself but rather to the latent benefits or utilities enabled through fuel consumption, fulfilling a range of functions. Therefore, researchers often map these utilities into observable variables within a latent variable model, be it continuous or discrete, recognizing the challenge of directly observing such utilities (Asfaw et al., 2012). Expressing such an economic cost in terms of indirect utility can be articulated as follows: $V(p, y - CV, d^1) = V(p, y, d^0)$, where p stands for the unit price of fossil fuel, y signifies the income level, CV represents the sum disregarded for the benefits derived from fuel-related functions, typically as compensating variation (CV), d^1 denotes the occurrence of fuel usage, and d^0 reflects the absence of fuel usage. The price, p , is assumed to be constant across all households. CV indicates the maximum amount of money the household is willing to sacrifice while ensuring it remains as well-off as it was before refraining from fuel usage (Saz-Salazar and Rausell-Koster, 2008).

q does not factor into the utility function (1) for nonparticipants and considering a positive price p , the optimal quantity for q is rendered zero. In the case of a participant, optimization entails solving a constrained utility maximization problem:

$$\max_{q,c} \{U(q, c; s) | pq = m\} \quad (3)$$

We denote demand for q as q^* , which represents the optimal quantity without the non-negativity constraint. Expressing latent demand expenditure (y^*), we can formulate it as follows:

$$y^* = x'\beta + v \quad (4)$$

where x and β are vectors of variables and parameters, respectively, and v is random disturbance, and the price of car fuel is not included in the single cross-section data and is absorbed into the constant term within the variables related to the household head and household (Coruh et al., 2022).

Although economic theory may not provide definitive guidance on the appropriate functional form for statistical relationships, empirical evidence, particularly when robust econometric procedures are followed, examines the types of monthly fossil fuel expenditure households generate. A characteristic feature of such microdata, assessed at the individual or family level, is the inevitable occurrence of zero observations of expenditure variables. These instances of zero observations stem from various factors. For instance, within the specific scope of our research, zero expenditure on passenger cars may be reported if a family owns alternative vehicle types. Similarly, zero expenditure on private fuel may be reported if a family has children who have moved out but still reside in the same province and own a passenger car. Alternatively, it is more probable that the family simply does not own any vehicles, including passenger cars, leading to unavoidable zero expenditure. These examples represent only a subset of potential cases, and in general, statistical analyses that overlook such “censoring” tend to jeopardize inconsistent empirical estimates.

To address this issue, robust results can be obtained by incorporating censoring into dependent variables using limited dependent variable models, such as the sample selection (SS) model and the double-hurdle model. The present implementations of these models rely heavily on bivariate normality distributions for the error terms. In the context of this study, we opted for the error-dependent DH censoring model as a benchmark and assessed its superiority over error-dependent single-hurdle (SH) censoring and SS models.

The DH censored model features one stochastic process $z'_i\alpha + u_i$ governing selection and an additional process $x'_i\beta + v_i$ governing level (which can be censored), such that, for observation i ,

$$y_i = x'_i\beta + v_i \text{ if } z'_i\alpha + u_i > 0 \text{ and } x'_i\beta + v_i > 0 \quad (5)$$

$$= 0 \text{ otherwise}$$

where z_i and x_i are vectors of explanatory variables that explain the binary spending decision and spending level decision, respectively, α and β are corresponding conformable parameter vectors, and the error terms (u_i, v_i), specific to each equation and occurring outside the control of the researcher are assumed to be distributed as bivariate normal with means $(0, 0)$, standard deviations $(1, \sigma)$, correlation ρ , and covariance $\rho\sigma$.

Typically, when modeling the fuel expenditure for private cars within a household, it is more suitable to initiate the process with two decision steps. In the initial decision step, the decision regarding private fuel spending is influenced by social and behavioral stimuli ($z'_i\alpha + u_i$). Subsequently, in the second stage, the decision regarding the amount of spending is causally connected to economic factors, such as budget constraints ($x'_i\beta + v_i$). For maximum likelihood estimation, the sample likelihood function for the DH censored model was utilized.

$$L = \prod_{y_i=0} \{1 - \Phi_2(z'_i\alpha, x'_i\beta / \sigma, \rho)\} \quad (6)$$

$$\times \prod_{y_i > 0} \left\{ \sigma^{-1} \phi \left[\frac{\mathbf{y}_i - \mathbf{x}'_i \boldsymbol{\beta}}{\sigma} \right] \Phi \left[\frac{\mathbf{z}'_i \boldsymbol{\alpha} + \rho [\mathbf{y}_i - \mathbf{x}'_i \boldsymbol{\beta}] / \sigma}{(1 - \rho^2)^{1/2}} \right] \right\}$$

where ϕ is the probability density function and Φ the cumulative distribution function of the standard normal distribution, and Φ_2 is the standard bivariate cumulative distribution function.

An important issue with the use of an endogenous selection model is the use of exclusion restrictions for parameter identification. This was accomplished by including unique variables in the selection equation ($\mathbf{z}'_i \boldsymbol{\alpha}$) (e.g., household factors such as stove and property category) that are excluded from the level equation as demand theory dictates, drawing on the random utility theory (Pudney, 1989). Although not essential for identification, household income group variables were only included in the level equation ($\mathbf{x}'_i \boldsymbol{\beta}$). Applying the parametric constraint $\rho = 0$ to the model results in an independent, two-part DH. Because the DH, SH, and SS models were non-nested, the Vuong z-test was used to statistically compare these models.

To exert the direction and effects of the explanatory variables on spending and level decisions, the positive observation probability and unconditional mean of the spending level are, respectively:

$$\Pr(\mathbf{y}_i > 0) = \Phi_2(\mathbf{z}'_i \boldsymbol{\alpha}, \mathbf{x}'_i \boldsymbol{\beta} / \sigma, \rho) \quad (7)$$

$$\begin{aligned} E(\mathbf{y}_i) = & \mathbf{x}'_i \boldsymbol{\beta} + \sigma [\Phi_2(\mathbf{z}'_i \boldsymbol{\alpha}, \mathbf{x}'_i \boldsymbol{\beta} / \sigma, \rho)]^{-1} \left\{ \left(\phi(\mathbf{x}'_i \boldsymbol{\beta} / \sigma) \Phi \left(\frac{\mathbf{z}'_i \boldsymbol{\alpha} - \rho(\mathbf{x}'_i \boldsymbol{\beta} / \sigma)}{(1 - \rho^2)^{1/2}} \right) \right) \right. \\ & \left. + \rho \phi(\mathbf{z}'_i \boldsymbol{\alpha}) \Phi \left(\frac{\mathbf{x}'_i \boldsymbol{\beta} / \sigma - \rho \mathbf{z}'_i \boldsymbol{\alpha}}{(1 - \rho^2)^{1/2}} \right) \right\} \end{aligned} \quad (8)$$

and the conditional mean is obtained by

$$E(\mathbf{y}_i | \mathbf{y}_i > 0) = E(\mathbf{y}_i) / \Pr(\mathbf{y}_i > 0) \quad (9)$$

using equations (7) and (8). The marginal effects of the continuous (binary) explanatory variables can be obtained by differentiating equations (7)–(9): All marginal effects were calculated for each observation and averaged over the sample. For statistical inference, the standard errors of the (average) marginal effects are derived using a mathematical approximation procedure known as the delta method.

4. Results

4.1. Preliminary results

Table 1 presents the sociodemographic and economic characteristics of households and household heads, along with the expenditure variables. In 2019, households, on average, expended 44.54 Turkish Liras (₺) weekly on gasoline, diesel, and LPG.⁴ Notably, the average expenditure for those utilizing these fuel types was 84.77₺.⁵ A total of 6131 Turkish families do

⁴ Mean equivalent CO₂ emission value for an average family in Türkiye can be derived from the given information. For instance, in 2019, the average unit prices for diesel, gasoline, and LPG were recorded as 6.43, 6.60, and 3.75₺, respectively (EMRB, 2020). If the monthly expenditure of an average family on diesel, gasoline, and LPG is denoted as y_1 , y_2 , and y_3 , and considering that diesel, gasoline, and LPG emit 2.68, 2.31, and 1.51 kg of CO₂ per liter, respectively, the total CO₂ emissions caused by the consumption of fossil fuels by an average family can be expressed as CO₂ quantity = (2.68/6.43)* y_1 + (2.31/6.60)* y_2 + (1.51/3.75)* y_3 . Based on this equation, an average family in the country produces 69.94 kg of CO₂ per month, whereas for families using fossil fuels, this value increases to 133.12 kg of CO₂. The equivalent CO₂ emissions, obtained through the same double-hurdle censored regression analysis, have been correlated with both the head of the household and the distinctive traits of the family. The outcomes are presented in the Appendix tables for interested readers.

⁵ The average USD exchange rate in Türkiye in 2019 was 5.68₺.

Table 1
Variable definitions and sample statistics.

Variable	Definition	Mean (SD)	VIF
Dependent variable			
Expenditure	Weekly fuel expenditure in Turkish Lira (₺) per month	44.536 (63.445)	
	Among the (48.6% of the sample)	84.767 (65.202)	
Household head characteristics: binary variables (yes = 1, no = 0)			
Cohort < 65	1 if the individual was born in 1965 or earlier, 0 otherwise (reference group)	0.428	–
Cohort 1965–1980	1 if the individual is in the 1965–1980 age group, 0 otherwise	0.344	2.201
Cohort > 1980	1 if the individual was born after 1980, 0 otherwise	0.228	2.719
Male	Gender is male	0.775	2.096
Unmarried	Never married	0.048	1.718
Divorced	Divorced	0.051	1.706
Widow	Widow	0.101	2.683
Married	Married (reference)	0.799	–
No School	Not holding a diploma (reference)	0.119	–
Elementary	Has elementary school education	0.398	3.202
Secondary	Has secondary school education	0.137	2.406
High school	Has high school education	0.167	2.904
College	Has college and higher (master or PhD) education	0.178	3.618
Salaried	Salaried, paid or full time or part-time employees	0.421	3.962
Employer	Employer or full and part-time self-employed	0.210	3.391
Retired	Retired	0.213	2.716
Other job status	Other job status (e.g., disabled and/or unable to work due to permanent health problems, housework, compulsory military service, and other conditions) (reference)	0.130	–
Agricultural job	Working in agriculture	0.181	1.893
Household characteristics: binary variables (yes = 1, no = 0)			
Greene card	Health expenses covered by the state	0.109	1.406
State aids	Receives cash or in-kind aid from government	0.260	1.653
Private aids	Receives cash or in-kind aids from private person and/or intuitions	0.171	1.119
Apartments	Resides in an apartment	0.561	2.214
Homeowner	Reference group	0.610	–
Tenant	Resides in a rental house	0.247	1.399
Other housing types	Slums and other housing types (reference group)	0.143	–
Spouses only	Family consisting of only spouses	0.194	3.115
Spouses with kids	Family consisting of spouses and kids	0.487	3.100
Other family types	At least one nuclear family and other members or more than one member without a nuclear family (reference)	0.319	–
Stove heating	House with traditional stove heating	0.452	2.083
Residence area	House with a living area of more than 160 square meters	0.051	1.065
Credit card(s) habit	Families with the habit of using credit cards	0.528	1.490
Eating out habit	Families with the habit of having food away from home	0.505	1.409
Cinema habit	Families with the habit of going to the cinema	0.092	1.229
Newspaper habit	Families with the habit of occasional reading of newspapers	0.051	1.082
Game habit	Families with the habit of playing game	0.043	1.047
Coffee house habit	Families with the habit of frequently going to coffee house	0.283	1.146
Bazaar habit	Families with the habit of going to Bazaar frequently	0.613	1.115
Internet habit	Families with an Internet connection at home	0.142	1.409
First quartile income	Family income less than 2477.17 ₺ per month (reference)	0.250	–
Second quartile income	Family income between 2477.17 and 3712.50 ₺ per month	0.250	1.816

(continued on next page)

Table 1 (continued)

Variable	Definition	Mean (SD)	VIF
Third quartile income	Family income between 3712.50 and 5595.47 ₺ per month	0.250	2.260
Fourth quartile income	Family income greater than 5595.47 ₺ per month	0.250	2.231
Household characteristics: continuous variables			
Number of properties	Number of properties owned (number of self-contained houses, number of summer houses, shops, etc.)	1.047 (1.260)	1.339
Kids	Number of children	0.982 (1.277)	1.712
Adults	Number of adults	2.413 (1.041)	2.159
Working persons	Number of working members in the family	1.185 (0.943)	2.668
Sample size	11142	-	-

Note: Standard deviations, in parentheses, are reported for continuous variables only.

not own a personal vehicle but spend approximately 8.74₺ per month on fuel. These families are likely to share their fuel expenses with close relatives living separately. In contrast, 4698 families owned private passenger cars and incurred a monthly fuel expenditure of 84.17₺. Vehicle ownership among Turkish families generally does not extend beyond two vehicles, with only 299 families owning two cars and spending an average of 150.21₺. Three- and four-vehicle ownership is extremely rare, with only 11 and 3 families reporting such ownership with an average fuel expenditure of 167.99₺ and 154.59₺, respectively. Conversely, the heads of households belonging to the baby boomer generation spend an average of 79.22₺ monthly on fossil fuel consumption for their private vehicles, whereas households led by X- and Y&Z-cohort heads spend 90.11₺ and 85.20₺, respectively. Noticeably, there are significant disparities in spending among households led by heads from different generations, indicating a non-linear relationship. Homes led by younger generation heads exhibit lower fossil fuel expenditures, thus contributing to less environmental pollution.

Considering the journal's word limit, we prioritized presenting the model results directly to the readers rather than delving into the descriptive statistical values of the independent variables used in the model. Although it is valuable to refer to Table 1 for descriptive statistics, we focus primarily on the classification of the family head cohort variables. Upon analyzing the birth years of individuals within the sample, the distribution was as follows: 43% for those born before 1965 (e.g., baby boomers), 34% for individuals born between 1965 and 1980 (e.g., X cohorts), and 23% for those born in 1980 and later (e.g., Y&Z cohorts). Table 1 also provides the Variance Inflation Factor (VIF), which quantifies the increase in variance of an estimated regression coefficient if the explanatory predictors are correlated. All the calculated VIF values were <5, indicating that the explanatory variables were not significantly correlated with each other.

4.2. Specification tests and model's results

All VIFs fell considerably below the accepted threshold of 10.0, indicating the absence of multicollinearity issues in the selection or level equations. Competing models with the same distribution (i.e., normal) but different structures (truncation), such as the SH and SS models, have emerged alongside the DH.⁶ Because these three models are not nested, Vuong's (1989) non-nested specification test was employed to distinguish between them. The SS model performs significantly worse than the DH (Vuong's standard normal statistic $z = -28.56$, $p\text{-value} < 0.001$) and SH ($z = -2.48$, $p\text{-value} < 0.05$). The statistical superiority between DH and SH belongs to the DH with a z -value of 2.48, indicating that

simultaneous spending decisions and spending amounts are interrelated. Consequently, the DH was retained for further analysis.

Also, based on the DH, Wald test results suggest rejection of $\rho = 0$ ($\chi^2 = 15.50$, $df = 1$), with a $p\text{-value} < 0.05$, favoring the fully parameterized error-dependent DH over the two-part DH model. The instruments used in the selection equation (i.e., the green card headed of households, residential area, heating system [stove], and property variables) showed significance with the Wald test ($\chi^2 = 67.7$, $df = 4$, $p\text{-value} < 0.05$), which rejects the weak instrument hypothesis and implies adequate instrumentation for parameter identification. The three distinct income variables in the level equation were jointly significant ($\chi^2 = 493.30$, $df = 3$, $p < 0.05$), confirming their inclusion. Finally, Wald test results showed that the explanatory variables were jointly significant in the decision ($\chi^2 = 275.10$ and $df = 35$) and level ($\chi^2 = 1659.20$ and $df = 34$) equations, all with a $p\text{-value} < 0.000$ (Table 2).

The significantly negative correlation coefficient between the errors suggests that unobserved factors exert opposing influences on binary (whether to spend) and level (how much to spend) decisions. In addition, although the parameter estimates are generally in accordance with economic theory, the signs of the parameters pertaining to certain factors exhibit discrepancies between the spending decision and spending level equations. This highlights the efficacy of the ability of the DH to capture the nuanced relationship between factors influencing expenditure patterns. In addition, because the probability and conditional and unconditional mean expectations derived from the model are not linear, the marginal effects with their standard errors were obtained by differentiating (differencing) equations (3)–(5) and averaging over the sample. The subsequent discussion focuses on the (average) marginal effects. The marginal effects of the explanatory variables on the probability of spending and on the level of spending are shown in Table 3. Compared to the reference group (e.g., baby boomer-headed households), households headed by individuals from Generation X exhibited a 4.88% higher likelihood of spending on private fuel (gasoline, diesel, and LPG used in transportation). Additionally, cohort X-headed households demonstrated higher monthly expenditure levels, both conditionally (4.87₺) and unconditionally (6.77₺), than the reference group. Similar results were observed for households headed by individuals from Generations Y and Z (Y&Z). The likelihood of incurring private fuel expenses and the unconditional expenditure level were higher by 7.80 percentage points and 3.86₺, respectively, in male-headed households than in female-headed households. However, households headed by individuals who had never been married exhibited a 7.03% lower probability of private fuel expenditure and an 8.07₺ lower unconditional expenditure level than households headed by married individuals. Meanwhile, compared to the reference group, households with a divorced head were 6.77% less likely to incur expenses related to private fuel and had a 9.99₺ lower unconditional spending level.

A compelling correlation exists between the probability and level of unconditional expenditure among households headed by individuals with varying educational backgrounds. As the educational attainment of household heads escalates, the likelihood of households incurring private fuel expenses and their expenditure levels increase significantly. This upward trend in the probabilities of private fuel expenditure and unconditional spending persists as the level of education progresses from primary to tertiary education. Notably, households headed by individuals with university education exhibited a significantly higher probability of private fuel expenditure (11.47 percentage points), conditional spending level (19.81₺), and unconditional spending level (21.51₺) than the reference group.

Households headed by salaried individuals, whether full- or part-time, are less likely to incur private fuel expenses (2.96 points lower) than the reference group. Conversely, employer-headed households exhibited higher expenditure levels, with conditional and unconditional expenditures reaching 12.90₺ and 11.09₺, respectively. Retired-headed households also displayed elevated expenditure levels, with an increase

⁶ Results of these models are available upon request.

Table 2

Maximum likelihood estimates of the double-hurdle censored regression for household fossil fuel usage.

Variable	Selection		Level		—
	Estimate	S.E.	Estimate	S.E.	
Constant	0.108	0.329	45.441 ***	11.220	
Cohort 1965–1980	0.202	0.128	9.219 **	3.772	
Cohort >1980	0.528 ***	0.166	3.767	4.754	
Male	0.947 ***	0.120	-17.619 ***	5.428	
Unmarried	-0.346 *	0.184	-9.166	8.661	
Divorced	0.094	0.189	-22.166 **	9.076	
Widow	0.148	0.200	-10.136	8.144	
Elementary	-0.171	0.195	18.366 ***	5.874	
Secondary	-0.305	0.228	29.317 ***	6.767	
High school	-0.391 *	0.220	31.013 ***	6.705	
College	-0.194	0.228	42.785 ***	6.720	
Salaried	-0.482 ***	0.161	6.745	6.071	
Employer	-0.453 **	0.186	31.766 ***	6.355	
Retired	-0.493 ***	0.165	18.153 ***	6.268	
Agricultural job	0.219	0.188	8.945 **	4.191	
State aids	0.028	0.127	-15.550 ***	4.012	
Private aids	-0.195 *	0.109	-2.826	3.928	
Apartments	-0.274 **	0.134	-13.103 ***	3.258	
Tenant	-0.165	0.107	0.014	3.537	
Spouses only	0.436 **	0.180	-4.960	6.020	
Spouses with kids	0.549 ***	0.138	-5.374	4.674	
Credit card(s) habit	0.338 ***	0.108	24.770 ***	3.171	
Eating out habit	-0.048	0.104	16.011 ***	2.936	
Cinema habit	-0.032	0.116	9.092 **	3.957	
Game habit	-0.078	0.176	-12.178 **	5.835	
Coffee house habit	0.127	0.096	6.564 **	2.718	
Bazaar habit	0.245 ***	0.087	0.664	2.725	
Internet habit	0.040	0.115	14.433 ***	3.505	
Newspaper habit	-0.124	0.146	1.202	4.941	
Kids	0.070	0.049	-0.369	1.128	
Adults	-0.049	0.056	-1.030	1.729	
Working persons	0.190 **	0.077	-1.560	1.966	
Greene card	-0.842 ***	0.124	—	—	
Stove heating	0.031	0.096	—	—	
Residence area	0.754 ***	0.269	—	—	
Number of properties	0.305 ***	0.058	—	—	
Second quartile income	—	—	28.093 ***	3.236	
Third quartile income	—	—	49.514 ***	3.438	
Fourth quartile income	—	—	81.747 ***	3.832	
Error std. dev. (σ)	—	—	81.177 ***	0.985	
Error correlation (ρ)	-0.329 ***	0.077	—	—	
Log-likelihood	-37,295.340				
Wald (df)[p-value]	275.10 (35)[<0.001]		1659.20 (34)[<0.001]	—	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Wald tests are for joint significance of all variables in equation.

of 6.25₺. Notably, households headed by agricultural workers have a positive influence on the likelihood and the level of private fuel expenditure. Conversely, households receiving government-provided cash or in-kind assistance exhibited lower private fuel expenditure probabilities of 5.08 percentage points, 6.62₺, and 7.56₺ for conditional, unconditional, and overall expenditures, respectively. Similarly, households receiving in-kind or cash assistance from private sources are less likely to incur private fuel expenses and have lower spending levels. Apartment-dwelling households were 7.14 percentage points less likely to spend on private fuel, with conditional and unconditional expenditure levels of 6.87₺ and 9.42₺ lower, respectively, compared to households residing in other housing types. Similar results were observed for households living in rental accommodations. A positive correlation was identified between the number of children in a household and the probability of private fuel expenditure as well as the level of spending.

The use of credit cards for private fuel expenditure is notably associated with increased spending patterns among households. This observation is supported by the higher probability of private fuel expenditure (12.46 percentage points), conditional expenditure level (12.12₺), and unconditional expenditure level (16.06₺) among households using credit cards compared to those not using credit cards.

Table 3

Marginal effects of explanatory variables on both the probability and spending levels of households using fossil fuels.

Variable	Probability		Conditional level		Unconditional level	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Cohort 1965–1980	5.216 ***	1.103	4.870	1.465	6.773 ***	1.547
Cohort >1980	6.298 ***	1.320	3.460 *	1.894	6.623 ***	2.025
Male	7.795 ***	1.500	-3.657 *	2.116	3.857 **	1.871
Unmarried	-7.028	2.212	-5.320 *	3.098	-8.073	3.045
Divorced	-6.774	2.390	-8.920	3.175	-9.993	3.306
Widow	-2.046	2.077	-3.883	3.028	-3.834	3.159
Elementary	4.190 ***	1.497	7.626	2.174	7.700 ***	2.042
Secondary	5.542 **	2.222	12.608	2.726	12.025	2.672
High school	5.016 **	2.213	12.971	2.703	11.816	2.670
College	11.472	2.285	19.810	2.914	21.510	2.996
Salaried	-2.960 *	1.537	1.191	2.324	-1.325	2.270
Employer	4.421 **	2.078	12.897	2.663	11.089	2.635
Retired	-0.170	1.651	6.245 **	2.480	3.629	2.268
Agricultural job	5.240 ***	1.436	4.835	1.625	6.832 ***	1.807
State aids	-5.081	1.078	-6.618	1.411	-7.555	1.442
Private aids	-3.103	1.040	-1.991	1.445	-3.405	1.434
Apartments	-7.143	1.081	-6.865	1.242	-9.422	1.367
Tenant	-1.788 *	1.020	-0.616	1.311	-1.642	1.373
Spouses only	2.434	1.581	0.743	2.291	1.192	2.438
Spouses with kids	4.148 ***	1.276	-0.344	1.745	2.812	1.769
Credit card(s) habit	12.460	0.944	12.123	1.125	16.057	1.157
Eating out habit	4.982 ***	0.883	6.905	1.086	7.809 ***	1.147
Cinema habit	2.682 **	1.274	4.014 **	1.652	4.473 **	1.825
Game habit	-4.925	1.586	-5.497	2.048	-6.732	2.093
Coffee house habit	3.539 ***	0.841	3.405	1.055	4.654 ***	1.138
Bazaar habit	2.871 ***	0.782	1.213	1.003	2.782 ***	1.032
Internet habit	5.270 ***	1.147	6.772	1.464	8.138 ***	1.626
Newspaper habit	-0.968	1.566	0.061	1.944	-0.643	2.100
Kids	0.615	0.391	0.094	0.451	0.490	0.479
Adults	-0.862 *	0.500	-0.638	0.658	-1.005	0.689
Working persons	1.471 **	0.670	0.003	0.748	1.031	0.816
Green card	-11.474	1.816	-3.868	1.098	-10.547	1.690
Stove heating	0.322	1.003	0.113	0.352	0.296	0.921
Residence area	5.928 ***	1.428	2.145	0.756	5.517 ***	1.366
Number of properties	3.200 ***	0.543	1.117	0.330	2.944 ***	0.508
Second quartile income	9.044 ***	0.993	13.111	1.586	14.986 ***	1.777
Third quartile income	16.103	1.076	23.732	1.790	27.155	1.981
Fourth quartile income	26.727	1.257	40.997	2.202	47.849 ***	2.451

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Similarly, a causal relationship was observed between the probability of households dining out and private fuel expenditure. The conditional and unconditional expenditure levels in this scenario are higher by 4.98 percentage points, 6.91₺, and 7.81₺, respectively. Likewise, households with a moviegoing habit display an unconditional private fuel expenditure level that is 4.47₺ higher than those without such a habit. However, households with gaming habits showed a decrease in the probability of private fuel expenditure, and conditional and unconditional expenditure levels, by 4.93 percentage points, 5.50₺, and 6.73₺, respectively. Notably, coffee shop habits increased the likelihood of households spending on private fuel and their unconditional spending levels by 3.54 percentage points and 6.65₺, respectively. Furthermore, a positive correlation was observed between households' habits of going to the bazaar and using the Internet, and the probability and level of private fuel expenditure.

A one-person increase in the household workforce size is associated with a 1.47-point increase in the probability of private fuel expenditure. Households with a green card exhibited a lower likelihood of private fuel expenditure (11.47 points), conditional expenditure (3.87₺), and unconditional expenditure levels (10.55₺) than households without this card. Additionally, residing in homes equipped with stoves negatively affects the probabilities of private fuel expenditure and unconditional expenditure. In addition, a positive relationship exists between the size of a household's residence (square meters, m^2) and the likelihood of private fuel expenditure (5.92 points), conditional expenditure (2.15₺), and unconditional expenditure levels (5.52₺). Additionally, as the number of properties owned by households increases, the management and follow-up tasks related to renting, selling, or other transactions involving these properties may positively impact private fuel expenditure.

As household income shifts from the second-quarter income group to the highest-income group, the probability of private fuel expenditure increases along with the conditional and unconditional spending levels. Households in the fourth-quarter income group exhibited a 26.73% higher probability of spending on private fuel than those in the first-quarter income group (the reference group). Their conditional and unconditional spending levels were also higher, at 41₺ and 48.85₺, respectively.

5. Discussion of findings

Our study employs an extensive cross-sectional analysis to explore the effects of household dynamics on fuel expenditure, with the focal aim of shaping robust policies for curbing carbon emissions at the bottom-up level (i.e., the household level), both in Türkiye and analogous countries. Beyond mere operational metrics, we also probed the relationship between the generational dynamics among household heads. Within this framework, we observed a pronounced inclination towards fuel consumption in households led by males, primarily attributable to their greater vehicle ownership and propensity for longer commutes. Interestingly, research underscores the distinct travel patterns among women, encompassing variability in distance-covered and transportation modalities chosen (Gauvin et al., 2020; Goel et al., 2021, 2023). Notably, women tend to undertake fewer drives on average (Havet et al., 2021), translating into comparatively lower fuel expenditures in female-headed households when juxtaposed with their male-led counterparts (Fiagborlo et al., 2023). Conversely, the lower monthly fuel consumption observed in households led by individuals who have never married can be attributed to the relative scarcity of external errand factors within the family unit, consistent with the findings of Fiagborlo et al. (2023), who reported a tendency for unmarried individuals to exhibit lower fuel consumption than their married counterparts. Households led by individuals who have never married or have divorced are typically single-person households, which generally tend to own smaller vehicles than households with married heads, potentially resulting in lower monthly expenditures on private

fuels.

Although a positive correlation has been established between CO₂ emissions and higher education (Brand et al., 2013), given the assumption that individuals with higher education levels are more environmentally conscious, it is plausible to assume that higher education may lead to lower CO₂ levels (Bel and Rosell, 2017). Our findings support the existing literature that associates intergenerational education levels with probability and expenditure levels. The analysis elicited a surprising pattern that deviated from the expected monotonically increasing trend, as highlighted above. Within age groups, as illustrated in Fig. 1, although there continues to be an increasing trend in fuel expenditure among highly educated and high-income households with Generation X heads, a decrease in private fuel expenditure begins to emerge among similarly educated and affluent households with Generation Y and Generation Z heads (Fig. 1). Conversely, the findings regarding the increase in the probability of monthly fuel consumption and fuel expenditure among households in which the head is employed align with international findings. Working individuals are generally associated with higher emissions, whereas housewives and retirees tend to generate lower emissions (Bel and Rosell, 2017). Moreover, households benefiting from governmental or private sector aid typically exhibit a diminished likelihood of monthly fuel expenditure and lower spending. This pattern emerges as these households allocate a larger proportion of their budgets to fundamental needs, such as food, reflecting their comparatively lower income levels and standard of living (Coruh et al., 2022). The results also suggest that living in an apartment correlates with reduced monthly fuel expenditure for households. Conversely, the presence of additional children in the family indicates a heightened necessity for external engagement, implying that family owned vehicles are utilized for longer periods, leading to increased expenditures. Interestingly, having a first child mitigates transportation emissions, whereas having a second child increases emissions (Büchs and Schnepf, 2013).

Households that make monthly fuel expenditures via credit cards possess a higher probability of significant spending and are likely to engage in greater expenditures. This propensity can be attributed to the various advantages associated with credit card payments among consumers, such as installment plans, deferments, and reward programs, which may incentivize higher spending (Eakins, 2016). A comparable spending trend emerges among families accustomed to dining out, where higher expenditures on private fuel coincide with their elevated social engagement and income, in contrast to those who opt for home-cooked meals, as highlighted by Cengiz et al. (2022). Moreover, in households with home Internet connectivity and specific shopping habits, such as frequenting bazaars, the likelihood and amount of monthly fuel expenditure tend to increase. These correlations are consistent with the findings of Olvera et al. (2008), who observed a similar connection between overall household spending and private fuel outlays. The emergence of Information and Communication Technologies (ICTs) has introduced alternative means of conducting activities that previously required physical travel, such as correspondence and remote shopping (Mokhtarian and Tal, 2013). The COVID-19 pandemic has accelerated the adoption of remote work practices (Barbieri et al., 2021) and the surge in online shopping and delivery services. Nevertheless, ICTs can optimize travel efficiency and cost-effectiveness through navigation tools that streamline routes, thereby enhancing travel allure (Mokhtarian, 2009). This dual role underscores the intricate relationship between technological advancement and travel behavior. The trend in monthly fuel consumption was influenced by the presence of an additional working member in the family. Such a discovery aligns with the anticipated escalation in transportation expenses with rising household income, and with economic theory (Cengiz et al., 2022). Moreover, Bayat et al. (2023) illustrated a positive correlation between per capita income in Türkiye and CO₂ emissions. Individuals with lower incomes, such as families that rely on stoves and hold green cards, exhibit reduced monthly fuel expenditures. Given that green card

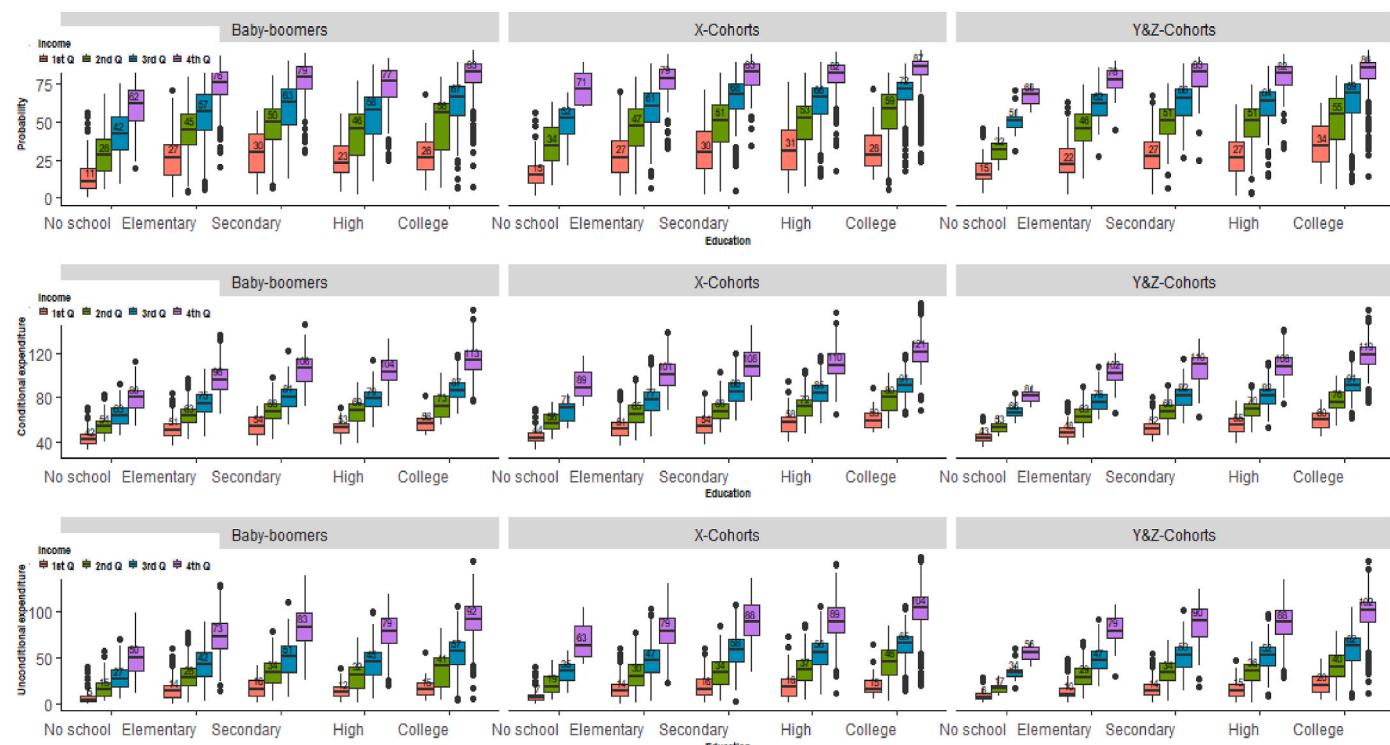


Fig. 1. Distributions of households' conditional and unconditional expenditures and probability levels across cohort, education types, and income levels.

ownership and reliance on stoves are indicative of poverty, these findings correspond with expectations. Bardazzi and Pazienza (2018) noted that households with elderly members spending more time at home allocate more resources to heating and fewer resources to transportation. Additionally, Olvera et al. (2008) underscored the limited access to regular motorized transportation among impoverished populations. By contrast, a positive correlation was observed between household income and the likelihood of private fuel expenditure and expenditure levels (Figs. 1 and 2). In contrast to our findings, transportation expenditures comprise <15% of household income in high-income brackets, signaling a comparatively lighter financial burden (Gebremeskel et al., 2023). Additionally, per capita income exerts a significant influence on transportation demand (Cordera et al., 2015). When exploring the relationship among spending probability, conditional expenditure, and income in relation to the number of vehicles owned by a household, the influence of income variability was evident in spending probability and conditional expenditure, particularly among families with one or more vehicles (Fig. 2). Income, household size, and homeownership are independent factors influencing vehicle ownership (Zhao and Bai, 2019). As anticipated, the probability of transportation spending and conditional and unconditional spending levels increase with increasing income levels (Coruh et al., 2022). A positive correlation was observed between the number of properties owned by a household, including single-family homes, apartments, vacation homes, shops, and hotels, and their spending probabilities and levels. This finding is expected and consistent with economic theory, given that real estate ownership is a marker of wealth. In this context, the expansion of property ownership creates an economic scale within the household, providing an advantage in terms of personal vehicle expenditure.

5.1. Policy implications

Findings related to the educational attainment of household heads are promising and potentially linked to growing environmental consciousness among younger families. This can be partly explained by their

interest in and inclination towards electric vehicles as substitutes for traditional fossil fuel-powered cars. Furthermore, the results of three-way ANOVA analyses, which are not presented here, support these conclusions. For instance, although the likelihood of spending on fossil fuels is notably low among low-income families, the opposite trend emerges in high-income households, where spending probability and conditional expenditure show significant fluctuations. Although households with two or more vehicles spend an average of 80–100₺ per month, expenditures do not increase linearly with rising income levels. Instead, expenditure follows a semi-concave trajectory and, in some cases, even declines in high-income families, suggesting a possible shift towards more fuel-efficient consumption patterns. This trend implies that promoting the adoption of fuel-efficient vehicles or alternative transportation options (i.e., an environmentally friendly public transportation network) among high-income households could potentially lead to decreased fuel consumption.

Leveraging the attractiveness of credit card usage, a nationwide rollout of regular special discounts and cashbacks, specifically for credit card purchases, can be implemented, particularly through strategic partnerships between banks and fuel companies. Such an approach can effectively curb gasoline, diesel, and LPG fuel consumption, while simultaneously encouraging the adoption of energy-efficient vehicles. However, private fuel costs can be significantly mitigated by implementing urban planning strategies that enhance the appeal of walking and cycling for everyday errands, such as visiting restaurants, coffee shops, and markets. A land-use policy that prioritizes the co-development of transportation modes and minimizes the need for long-distance travel can effectively curb GHG emissions in Türkiye by discouraging households from relying heavily on private vehicles. Furthermore, the current study reveals a positive correlation between Internet usage habits and private fuel expenditure. Technological companies can promote applications, scoring systems, and rewards that encourage physical activity to mitigate these expenses. By adopting these policy recommendations, individuals can embrace a more active, healthy, and socially connected lifestyle, thereby counterbalancing the sedentary tendencies often associated with Internet usage. Interestingly,

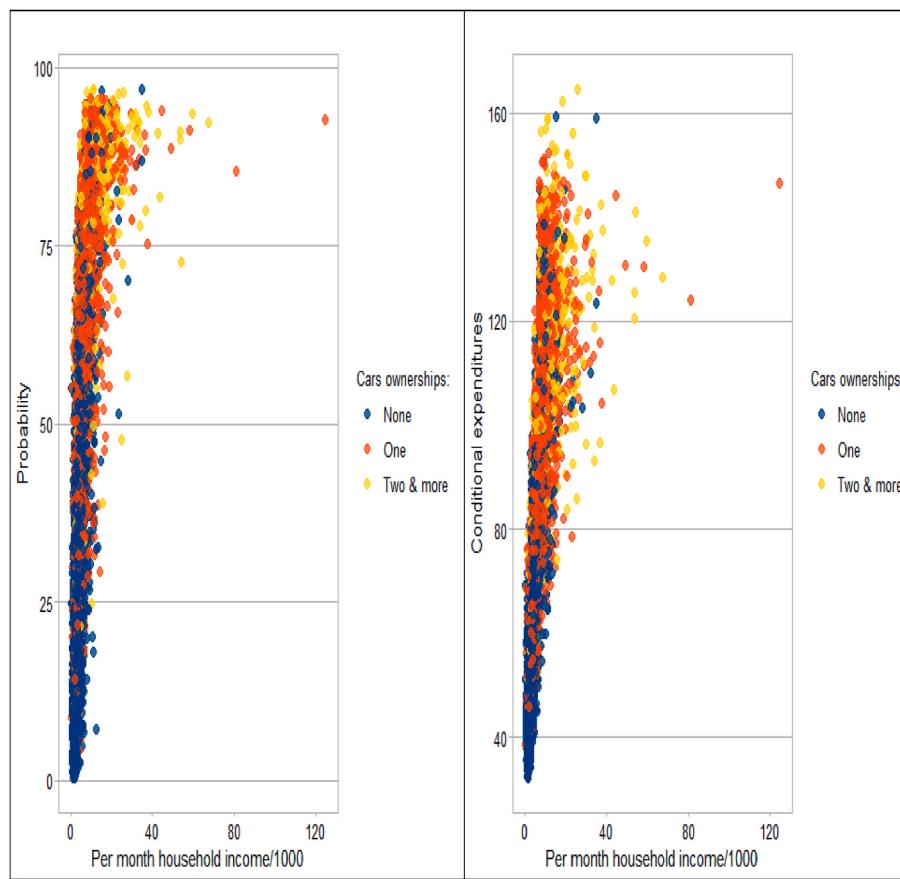


Fig. 2. Distributions of both probability and conditional expenditures on private vehicles.

this study also identified a positive association between housing sizes of 160 m² or larger and private fuel expenditure. This finding aligns with the well-established notion that travel preferences are shaped by their life stage (birth or marriage) and the size of their selected residence. Larger homes are often situated farther from urban centers, necessitating longer commutes to work, shopping, and other destinations. Consequently, urban planning and transportation infrastructure play pivotal roles in influencing emissions. Therefore, poorly planned cities characterized by sprawling suburbs and inadequate public transportation systems can inadvertently promote car usage and prolong commuting times. Sustainable transportation policies, when implemented in conjunction with sustainable land-use policies, can effectively limit household transportation budgets and alleviate the adverse impacts of economic crises on mobility. Therefore, investing in robust public transportation systems and designing cities that minimize the need for long-distance travel can emerge as powerful strategies for achieving emissions reduction targets. In this context, the expansion and modernization of public transportation networks, particularly in major cities, are of paramount importance. Bolstering eco-friendly public transportation options such as high-speed rail systems, light rail systems, and metro systems across the country can lay the foundation for sustainable transportation infrastructure and thus alleviate the pressure on emissions.

A strikingly positive correlation was observed between the number of properties owned by households and private fuel expenditure. The COVID-19 pandemic has further exacerbated this trend, triggering a surge in the demand for second homes situated away from densely populated urban centers. This explosion in the demand for suburban living could lead to increased investment in suburban development, potentially exacerbating reliance on private vehicles. Although the pandemic has undoubtedly encouraged cycling and walking, it has also

fostered a preference for individual travel modes owing to heightened concerns regarding the safety of public transport. To alleviate such concerns and foster a shift towards environmentally friendly transportation options, policymakers should implement a suite of incentives, including tax regulations and subsidy packages, for individuals who opt for sustainable vehicles that are recognized as more environmentally friendly. The energy ladder hypothesis is poised to unfold, notably within households led by the newer generation, characterized by elevated income levels and advanced education. As fossil fuel consumption tapers off, this ignites a ripple effect, fostering a heightened sense of environmental consciousness among family members. This effect was particularly pronounced in the younger cohort, showing a significant shift towards greener practices and sustainable energy choices.

Our findings suggest that to alleviate the pressure on fuel consumption and achieve the desired emission targets, it is essential to expand the public transportation network, which is generally seen as an environmentally friendly alternative to personal vehicles. However, this expansion ultimately requires substantial investments in technical infrastructure. In developing countries, where investments are largely centralized, decisions on where to place new transportation investments are often politically driven (Luca and Rodríguez-Pose, 2019). To effectively prioritize such investments, aligning them with the profile of typical public transport users (urban, middle-aged, working, retired, or with children) data mapping GHG concentrations and particulate matter from internal combustion engines must be utilized. For instance, even short-term exposure to air pollution has been found to increase respiratory problems in Istanbul and nearby industrial cities such as Bursa, Tekirdağ, and İzmit (Çapraz et al., 2017; Bayat et al., 2023). Considering regional climate and geographical variations, including emission intensity heat maps and taxonomies across different areas, prioritizing the

development of new public transportation routes focused on emission reduction could emerge as a powerful strategy in the green transformation battle. However, this requires a steadfast political will. Moreover, as each additional child in a family increases fuel consumption, it becomes paramount to reassess and prioritize effective short- and long-term population and family planning strategies to significantly mitigate emissions and alleviate environmental pressure.

6. Conclusion

The growing emphasis on formulating policies from the grassroots to the top-down to sustain the innovative path initiated by green transformation in the energy sector is becoming increasingly evident and significant with each passing day. In this context, this study establishes the connections between the sociodemographic and economic characteristics of households and private fuel expenditure probabilities and levels using a DH in censored models. Our study distinguishes itself uniquely by delving deeply into the intriguing nexus between household characteristics and monthly gasoline expenditure probabilities and levels. Utilizing a contemporary econometric model, we illuminate households as often-unnoticed yet pivotal hubs for CO₂ emissions, thus unveiling their profound impact as emission production centers. The analysis results indicate that household's socio-demographic and economic factors substantially impact determining private fuel expenditure and expenditure levels. This information is crucial for reinforcing innovative developments in the energy sector and developing market segmentation and marketing strategies based on socio-demographic and economic factors, private fuel expenditure opportunities, and household expenditure levels. Although approximately 25 out of the 38 independent variables exhibited a positive relationship with the probability and levels of private fuel expenditure, the remaining variables were found to have a negative relationship. Among the 25 positively correlated variables, 21 were statistically significant. In this context, analyses focusing on the sociodemographic and economic characteristics of household heads and members, going beyond one-dimensional relationships between individuals and offering a versatile and in-depth examination, can assist in achieving desired goals more effectively. For instance, rather than solely examining the education variable, understanding the relationships among variables such as income, education, and age by evaluating them together is crucial. By focusing on variables that increase the probability and quantity of private fuel expenditure, approaches of this nature can form the foundation for effective policies aimed at reducing such expenditures. For example, integrating energy efficiency and clean transportation topics into educational programs to increase environmental awareness among new generations and encourage sustainable transportation habits could be an effective policy tool. In this age group, certain tax exemptions, financial aid, or low-interest loans may be offered to encourage the purchase of electric vehicles, thereby reducing fossil fuel consumption. Therefore, by understanding the transport behavior patterns of households, these studies can accelerate the decarbonization process and contribute to the development of an intergenerational energy culture that embraces sustainable transport systems. In this context, it is imperative for governments to direct infrastructure investment towards innovative technologies.

This study conducts analyses and examinations in the context of CO₂ emissions reduction using household-level monthly fuel expenditure as its anchor. By leveraging the intrinsic relationship between fuel spending and CO₂ emissions, researchers are encouraged to explore the nuanced emission quantities linked to household characteristics, as shown in the Appendix. This approach provides deeper insights and fosters more meaningful correlations. Ultimately, this endeavor has the potential to furnish policymakers and industry stakeholders with robust findings, propelling concerted efforts towards a greener and more sustainable future. Future research could also focus on analyzing the dynamic relationship between fuel prices and the quantity demanded,

thereby uncovering effective policy instruments.

Table A1

Maximum-likelihood estimates of the double-hurdle censored regression for households' CO₂ emission.

Variable	Selection		Level		-
	Estimate	S.E.	Estimate	S.E.	
Constant	0.239	0.344	-82.044 ***	17.267	
Cohort 1965–1980	0.196	0.133	15.699 ***	5.930	
Cohort >1980	0.555 ***	0.173	6.700	7.477	
Male	1.018 ***	0.127	-28.963 ***	8.651	
Unmarried	-0.332 *	0.192	-18.136	13.510	
Divorced	0.171	0.199	-41.239 ***	14.045	
Widow	0.152	0.207	-16.526	12.763	
Elementary	-0.244	0.202	31.097 ***	9.061	
Secondary	-0.360	0.238	47.284 ***	10.476	
High school	-0.439 *	0.229	49.236 ***	10.398	
College	-0.229	0.239	66.797 ***	10.413	
Salaried	-0.565 ***	0.168	13.602	9.583	
Employer	-0.546 ***	0.194	54.202 ***	10.002	
Retired	-0.538 ***	0.173	29.766 ***	9.872	
Agricultural job	0.163	0.188	16.475 **	6.500	
State aids	0.034	0.131	-24.279 ***	6.272	
Private aids	-0.214 *	0.113	-3.821	6.183	
Apartments	-0.268 *	0.140	-21.113 ***	5.083	
Tenant	-0.167	0.112	-0.007	5.582	
Spouses only	0.406 **	0.188	-4.865	9.389	
Spouses with kids	0.549 ***	0.142	-7.439	7.289	
Credit card(s) habit	0.335 ***	0.113	39.905 ***	4.961	
Eating out habit	-0.061	0.109	25.941 ***	4.608	
Cinema habit	-0.041	0.123	12.954 **	6.315	
Game habit	-0.052	0.189	-20.855 **	9.163	
Coffee house habit	0.125	0.100	10.897 **	4.268	
Bazaar habit	0.265 ***	0.091	1.419	4.304	
Internet habit	0.020	0.120	22.997 ***	5.545	
Newspaper habit	-0.104	0.156	-0.080	7.784	
Kids	0.062	0.050	0.007	1.965	
Adults	-0.068	0.058	-0.521	2.737	
Working persons	0.209 ***	0.080	-2.854	3.114	
Greene card	-0.868 ***	0.128	-	-	
Stove heating	0.039	0.101	-	-	
Residence area	0.760 ***	0.287	-	-	
Number of properties	0.326 ***	0.063	-	-	
Second quartile income	-	-	44.713 ***	5.086	
Third quartile income	-	-	78.375 ***	5.401	
Fourth quartile income	-	-	128.273 ***	6.024	
Error std. dev. (σ)	-	-	128.770 ***	1.541	
Error correlation (ρ)	-0.330 ***	0.078	-	-	
Log-likelihood	-39,966.860				
Wald (df)[p-value]	252.30 (35)[<0.001]		1645.40 (34)[<0.001]		-

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Wald tests are for joint significance of all variables in equation.

Table A2

Marginal effects of explanatory variables on both the probability and levels of CO₂ emission.

Variable	Probability		Conditional level		Unconditional level	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Cohort 1965–1980	5.311 ***	1.095	8.050 ***	2.284	11.007 ***	2.440
Cohort >1980	6.375 ***	1.326	5.763 *	2.953	10.667 ***	3.202
Male	8.077 ***	1.533	-5.816 *	3.335	6.324 **	2.963
Unmarried	-7.430	2.196	-9.654	4.711	-13.837 ***	4.711
	***		**		***	
Divorced	-7.708	2.431	-15.984	4.771	-17.740 ***	5.087
	***		***		***	
Widow	-2.240	2.097	-6.288	4.687	-6.382	4.977
Elementary	4.016 ***	1.522	12.467	3.315	12.224 ***	3.197
	***		***		***	
Secondary	5.302 **	2.313	19.867	4.171	18.711 ***	4.264
	***		***		***	

(continued on next page)

Table A2 (continued)

Variable	Probability		Conditional level		Unconditional level	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
High school	4.778 **	2.282	20.132	4.137	18.202	4.242
		***		***	***	
College	11.159	2.341	30.358	4.454	32.071	4.731
	***		***		***	
Salaried	-2.934 *	1.554	2.756	3.613	-1.451	3.549
Employer	4.298 **	2.153	21.510	4.155	18.091	4.182
	***		***		***	
Retired	-0.188	1.695	10.044	3.843	5.871	3.577
	***		***		***	
Agricultural job	5.134 ***	1.421	8.304 ***	2.505	11.086	2.823
	***		***		***	
State aids	-5.029	1.070	-10.201	2.183	-11.734	2.267
	***		***		***	
Private aids	-3.060	1.039	-2.909	2.250	-5.160	2.259
	***		***		**	
Apartments	-7.054	1.077	-10.831	1.917	-14.740	2.143
	***		***		***	
Tenant	-1.703 *	1.021	-0.950	2.045	-2.460	2.171
Spouses only	2.587	1.577	-0.083	3.563	2.704	3.834
Spouses with kids	4.002 ***	1.268	-0.184	2.716	4.411	2.789
Credit card(s) habit	12.473	0.938	19.197	1.735	25.365	1.815
	***		***		***	
Eating out habit	5.069 ***	0.881	11.007	1.688	12.507	1.809
	***		***		***	
Cinema habit	2.341 *	1.286	5.582 **	2.596	6.197 **	2.894
Game habit	-4.925	1.593	-9.098	3.156	-10.978	3.288
	***		***		***	
Coffee house habit	3.539 ***	0.839	5.528 ***	1.638	7.486 ***	1.791
Bazaar habit	2.871 ***	0.781	2.124	1.565	4.633 ***	1.627
Internet habit	5.270 ***	1.153	10.559	2.290	12.612	2.570
	***		***		***	
Newspaper habit	-0.968	1.569	-0.627	3.006	-1.573	3.299
Kids	0.615	0.378	0.343	0.707	0.881	0.751
Adults	-0.862 *	0.493	-0.603	1.030	-1.232	1.086
Working persons	1.471 **	0.662	-0.101	1.172	1.507	1.288
Green card	-11.474	1.810	-6.104	1.756	-16.386	2.658
	***		***		***	
Stove heating	0.387	0.989	0.217	0.558	0.558	1.425
Residence area	5.560 ***	1.403	3.234 ***	1.177	8.115 ***	2.105
Number of properties	3.215 ***	0.551	1.799 ***	0.537	4.640 ***	0.810
Second quartile income	9.212 ***	0.999	20.665	2.471	23.868	2.798
	***		***		***	
Third quartile income	16.317	1.081	37.203	2.788	43.016	3.118
	***		***		***	
Fourth quartile income	26.943	1.265	63.605	3.420	75.059	3.856
	***		***		***	

Note: ***p < 0.01, **p < 0.05, *p < 0.10.

CRediT authorship contribution statement

Emine Coruh: Writing – original draft, Software, Conceptualization. **Abdulbaki Bilgic:** Writing – review & editing, Visualization, Validation, Software, Methodology. **Vedat Cengiz:** Validation, Software, Data curation. **Faruk Urak:** Supervision, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

- Aksoy, A., Bilgic, A., Yen, S.T., Urak, F., 2019. Determinants of household alcohol and tobacco expenditures in Turkiye. *J. Fam. Econ. Issues* 40 (4), 609–622. <https://doi.org/10.1007/s10834-019-09619-1>.
- Alajmi, R.G., 2021. Factors that impact greenhouse gas emissions in Saudi Arabia: decomposition analysis using LMDI. *Energy Pol.* 156, 112454 <https://doi.org/10.1016/j.enpol.2021.112454>.
- Ali, E.B., Shayammehr, S., Radmehr, R., Bayitse, R., Agbozo, E., 2024. Investigating environmental quality among G20 nations: the impacts of environmental goods and low-carbon technologies in mitigating environmental degradation. *Geosci. Front.* 15 (1), 101695 <https://doi.org/10.1016/j.gsf.2023.101695>.
- Andreoni, V., Galmarini, S., 2016. Drivers in CO₂ emissions variation: a decomposition analysis for 33 world countries. *Energy* 103, 27–37. <https://doi.org/10.1016/j.energy.2016.02.096>.
- Andrés, L., Padilla, E., 2018. Driving factors of GHG emissions in the EU transport activity. *Transport Pol.* 61, 60–74. <https://doi.org/10.1016/j.tranpol.2017.10.008>.
- Apergis, N., Li, J., 2016. Population and lifestyle trend changes in China: implications for environmental quality. *Appl. Econ.* 48 (54), 5246–5256. <https://doi.org/10.1080/00036846.2016.1173184>.
- Aristei, D., Pieroni, L., 2008. A double-hurdle approach to modelling tobacco consumption in Italy. *Appl. Econ.* 40 (19), 2463–2476. <https://doi.org/10.1080/0036840600970229>.
- Asfaw, S., Shiferaw, B., Simtowe, F., Lipper, L., 2012. Impact of modern agricultural technologies on smallholder welfare Evidence from Tanzania and Ethopia. *Food Pol.* 37 (3), 283–295. <https://doi.org/10.1016/j.foodpol.2012.02.013>.
- Ata, B., Pakrooh, P., Pénzes, J., 2023. Driving factors of energy related CO₂ emissions at a regional level in the residential sector of Iran. *Sci. Rep.* 13 (1), 17598 <https://doi.org/10.1038/s41598-023-44975-x>.
- Bai, Y., Deng, X., Gibson, J., Zhao, Z., Xu, H., 2019. How does urbanization affect residential CO₂ emissions? An analysis on urban agglomerations of China. *J. Clean. Prod.* 209, 876–885. <https://doi.org/10.1016/j.jclepro.2018.10.248>.
- Baiocchi, G., Minx, J., Hubacek, K., 2010. The impact of social factors and consumer behavior on carbon dioxide emissions in the United Kingdom. *J. Ind. Ecol.* 14, 50–72. <https://doi.org/10.1111/j.1530-9290.2009.00216.x>.
- Bannor, R.K., Amfo, B., Oppong-Kyeremeh, H., Hope, L., Kyire, S.K.C., Djimatey, R., 2022. Land tenure system and harvesting time's influence on the marketing behaviour of cashew farmers in the Bondo Region of Ghana. *Heliyon* 8, 211392. <https://doi.org/10.1016/j.heliyon.2022.e11392>.
- Barbieri, D.M., Lou, B., Passavanti, M., et al., 2021. Impact of COVID-19 pandemic on mobility in ten countries and associated perceived risk for all transport modes. *PLoS One* 16 (2), e0245886. <https://doi.org/10.1371/journal.pone.0245886>.
- Bardazzi, R., Pazienza, M.G., 2018. Ageing and private transport fuel expenditure: do generations matter? *Energy Pol.* 117, 396–405. <https://doi.org/10.1016/j.enpol.2018.03.026>.
- Barla, P., Miranda-Moreno, L.F., Lee-Gosselin, M., 2011. Urban travel CO₂ emissions and land use: a case study for Quebec City. *Transportation Research Part D: Transport and Environment* 16 (6), 423–428. <https://doi.org/10.1016/j.trd.2011.03.005>.
- Bayat, T., İlarslan, K., Shahbaz, M., 2023. How do logistics and financial indicators contribute to carbon emissions in Turkiye? *Environ. Sci. Pollut. Control Ser.* 1–15. <https://doi.org/10.1007/s11356-023-29255-5>.
- Bel, G., Rosell, J., 2017. The impact of socioeconomic characteristics on CO₂ emissions associated with urban mobility: inequality across individuals. *Energy Econ.* 64, 251–261. <https://doi.org/10.1016/j.eneco.2017.04.002>.
- Brand, C., Preston, J.M., 2010. '60–20 emission'—the unequal distribution of greenhouse gas emissions from personal, non-business travel in the UK. *Transport Pol.* 17, 9–19. <https://doi.org/10.1016/j.tranpol.2009.09.001>.
- Brand, C., Goodman, A., Rutter, H., Song, Y., Ogilvie, D., 2013. Associations of individual, household and environmental characteristics with carbon dioxide emissions from motorised passenger travel. *Applied energy* 104, 158–169. <https://doi.org/10.1016/j.apenergy.2012.11.001>.
- Brida, J.G., Scuderi, R., 2013. Determinants of tourist expenditure: a review of microeconometric models. *Tourism Manag. Perspect.* 6 (April), 28–40. <https://doi.org/10.1016/j.tmp.2012.10.006>.
- Büchs, M., Schneid, S.V., 2013. Who emits most? Associations between socio-economic factors and UK households' home energy, transport, indirect and total CO₂ emissions. *Ecol. Econ.* 90, 114–123. <https://doi.org/10.1016/j.ecolecon.2013.03.007>.
- Cao, Q., Kang, W., Xu, S., Sajid, M.J., Cao, M., 2019. Estimation and decomposition analysis of carbon emissions from the entire production cycle for Chinese household consumption. *J. Environ. Manag.* 247, 525–537. <https://doi.org/10.1016/j.jenvman.2019.06.044>.
- Cengiz, V., Bilgic, A., Yen, S.T., Efekan, E., 2022. Households' censored mobile phone spending and its determinants in Turkiye: an inverse-hyperbolic sine double-hurdle model. <https://doi.org/10.21203/rs.3.rs-1374011/v1>.
- Christis, M., Breemersch, K., Vercalsteren, A., Dilis, E., 2019. A detailed household carbon footprint analysis using expenditure accounts – case of Flanders (Belgium). *J. Clean. Prod.* 228, 1167–1175. <https://doi.org/10.1016/j.jclepro.2019.04.160>.

- Cordera, R., Canales, C., Dell'Olio, L., Ibeas, A., 2015. Public transport demand elasticities during the recessionary phases of economic cycles. *Transport Pol.* 42, 173–179. <https://doi.org/10.1016/j.tranpol.2015.05.022>.
- Coruh, E., Urak, F., Bilgic, A., Yen, S.T., 2022. The role of household demographic factors in shaping transportation spending in Turkiye. *Environ. Dev. Sustain.* 24 (3), 3485–3517. <https://doi.org/10.1007/s10668-021-01575-x>.
- Coruh, E., Bilgic, A., 2023. Sustainability and Environmental Impacts of Turkiye's Energy and Transportation Infrastructure: an Overview of Urbanization, Energy, and Emissions. Chapter V. BIDGE Publications (Turkish).
- Çapraz, Ö., Deniz, A., Doğan, N., 2017. Effects of air pollution on respiratory hospital admissions in Istanbul, Turkey, 2013–2015. *Chemosphere* 181, 544–550. <https://doi.org/10.1016/j.chemosphere.2017.04.105>.
- Dai, J., Alvarado, R., Ali, S., et al., 2023. Transport infrastructure, economic growth, and transport CO₂ emissions nexus: does green energy consumption in the transport sector matter? *Environ. Sci. Pollut. Res.* 30, 40094–40106. <https://doi.org/10.1007/s11356-022-25100-3>.
- Das, A., Paul, S.K., 2014. CO₂ emissions from household consumption in India between 1993–94 and 2006–07: a decomposition analysis. *Energy Econ.* 41, 90–105. <https://doi.org/10.1016/j.eneco.2013.10.019>.
- Ding, Q., Cai, W., Wang, C., Sanwal, M., 2017. The relationships between household consumption activities and energy consumption in China—an input-output analysis from the lifestyle perspective. *Appl. Energy* 207, 520–532. <https://doi.org/10.1016/j.apenergy.2017.06.003>.
- Dou, Y., Zhao, J., Dong, X., Dong, K., 2021. Quantifying the impacts of energy inequality on carbon emissions in China: a household-level analysis. *Energy Econ.* 102, 105502. <https://doi.org/10.1016/j.eneco.2021.105502>.
- Downward, P., Lumsdon, L., 2000. The demand for day-visits: an analysis of visitor spending. *Tourism Econ.* 6 (3), 251–261. <https://doi.org/10.5367/000000000101297622>.
- Downward, P., Lumsdon, L., 2003. Beyond the demand for day-visits: an analysis of visitor spending. *Tourism Econ.* 9 (1), 67–76. <https://doi.org/10.5367/000000003101298277>.
- Eakins, J., 2016. An application of the double hurdle model to petrol and diesel household expenditures in Ireland. *Transport Pol.* 47, 84–93. <https://doi.org/10.1016/j.tranpol.2016.01.005>.
- EIA, Energy Information Administration, 2019. International Energy Outlook 2019. U.S. Department of Energy, Washington, DC.
- Energy Market Regulatory Board (EMRB), 2020. Ankara, Turkiye. (Accessed 10 January 2020).
- Erdogdu, E., 2014. Motor fuel prices in Turkiye. *Energy Pol.* 69, 143–153. <https://doi.org/10.1016/j.enpol.2013.10.075>.
- Feng, K., Hubacek, K., Guan, D., 2009. Lifestyles, technology and CO₂ emissions in China: a regional comparative analysis. *Ecol. Econ.* 69, 145–154. <https://doi.org/10.1016/j.ecolecon.2009.08.007>.
- Fiagborlo, J.D., Obeng, C.K., Vondolia, G.K., 2023. Gender differences in spending on information and communication technology and transport fuel intensity: evidence from Ghana. *Heliyon* 9 (5), e16465. <https://doi.org/10.1016/j.heliyon.2023.e16465>.
- Gauvin, L., Tizzoni, M., Piaggesi, S., et al., 2020. Gender gaps in urban mobility. *Human. Social Sci. Commun.* 7 (1), 1–13. <https://doi.org/10.1057/s41599-020-0500-x>.
- Gebremeskel, E., Woldeamanuel, M., Woldetensae, B., 2023. Transport vulnerability: measuring travel time and expenditure budget in Addis Ababa. *Res. Transport. Econ.* 100, 101247. <https://doi.org/10.1016/j.retrec.2022.101247>.
- Gill, B., Moeller, S., 2018. GHG emissions and the rural-urban divide. A carbon footprint analysis based on the German official income and expenditure survey. *Ecol. Econ.* 145, 160–169. <https://doi.org/10.1016/j.ecolecon.2017.09.004>.
- Goel, R., Goodman, A., Aldred, R., et al., 2021. Cycling behaviour in 17 countries across 6 continents: levels of cycling, who cycles, for what purpose, and how far? *Transp. Rev.* <https://doi.org/10.1080/01441647.2021.1915898>.
- Goel, R., Oyebode, O., Foley, L., Tatah, L., Millett, C., Woodcock, J., 2023. Gender differences in active travel in major cities across the world. *Transportation* 50 (2), 733–749. <https://doi.org/10.1007/s11116-021-10259-4>.
- Guan, D., Klasen, S., Hubacek, K., Feng, K., Liu, Z., He, K., Geng, Y., Zhang, Q., 2014. Determinants of stagnating carbon intensity in China. *Nat. Clim. Change* 4 (11), 1017–1023. <https://doi.org/10.1038/nclimate2388>.
- Habib, Y., Xia, E., Hashmi, S.H., Ahmed, Z., 2021. The nexus between road transport intensity and road-related CO₂ emissions in G20 countries: an advanced panel estimation. *Environ. Sci. Pollut. Control Ser.* 28 (41), 58405–58425. <https://doi.org/10.1007/s11356-021-14731-7>.
- Hanemann, M., Labandeira, X., Labeaga, J.M., Vasquez-Lavin, F., 2024. Discrete-continuous models of residential energy demand: a comprehensive review. *Resour. Energy Econ.* 77 <https://doi.org/10.1016/j.reseneeco.2024.101426>.
- Hao, H., Geng, Y., Wang, H., Ouyang, M., 2014. Regional disparity of urban passenger transport associated GHG (greenhouse gas) emissions in China: a review. *Energy* 68, 783–793. <https://doi.org/10.1016/j.energy.2014.01.008>.
- Havet, N., Bayart, C., Bonnel, P., 2021. Why do gender differences in daily mobility behaviours persist among workers? *Transport. Res. Pol. Pract.* 145, 34–48. <https://doi.org/10.1016/j.tra.2020.12.016>.
- Huang, Y., Matsumoto, K.I., 2021. Drivers of the change in carbon dioxide emissions under the progress of urbanization in 30 provinces in China: a decomposition analysis. *J. Clean. Prod.* 322, 129000. <https://doi.org/10.1016/j.jclepro.2021.129000>.
- Hussain, M.M., Pal, S., Villanthenkodath, M.A., 2023. Towards sustainable development: the impact of transport infrastructure expenditure on the ecological footprint in India. *Innovation and Green Development* 2 (2), 100037. <https://doi.org/10.1016/j.igd.2023.100037>.
- Hussain, Z., Kaleem Khan, M., Xia, Z., 2023. Investigating the role of green transport, environmental taxes and expenditures in mitigating the transport CO₂ emissions. *Transportation Letters* 15 (5), 439–449. <https://doi.org/10.1080/19427867.2022.2065592>.
- IEA, 2019a. Transport Sector CO₂ Emissions by Mode in the Sustainable Development Scenario, 2000–2030 – Charts – Data & Statistics. IEA. <https://www.iea.org/data-and-statistics/charts/transport-sector-co2-emissions-by-mode-in-the-sustainable-development-scenario-2000-2030>. (Accessed 15 October 2023).
- IEA, 2019b. International energy agency. World Energy Balances: Overview. <https://webstore.iea.org/world-energy-balances-2019>. (Accessed 10 April 2022).
- Isik, M., Sarica, K., Ari, I., 2020. Driving forces of Turkiye's transportation sector CO₂ emissions: an LMDI approach. *Transport Pol.* 97, 210–219. <https://doi.org/10.1016/j.tranpol.2020.07.006>.
- ITF, 2019. Efficiency in railway operations and infrastructure management. In: ITF Roundtable Reports, vol. 177. OECD Publishing, Paris.
- Ivanova, D., Barrett, J., Wiedenhofer, D., Macura, B., Callaghan, M., Creutzig, F., 2020. Quantifying the potential for climate change mitigation of consumption options. *Environ. Res. Lett.* 15, 093001. <https://doi.org/10.1088/1748-9326/ab8589>.
- Ivanova, D., Stadler, K., Steen-Olsen, K., Wood, R., Vita, G., Tukker, A., Hertwich, E.G., 2016. Environmental impact assessment of household consumption. *J. Indust. Ecol.* 20 (3), 526–536. <https://doi.org/10.1111/jiec.12371>.
- Kahneman, D., Tversky, A., 1979. Prospect theory: an analysis of decision under risk. *Econometrica* 47, 363–391. <https://doi.org/10.2307/1914185>.
- Legras, S., Cavailhès, J., 2016. Environmental performance of the urban form. *Reg. Sci. Urban Econ.* 59, 1–11. <https://doi.org/10.1016/j.regsciurbeco.2016.03.002>.
- Li, Y., Zhao, R., Liu, T., Zhao, J., 2015. Does urbanization lead to more direct and indirect household carbon dioxide emissions? Evidence from China during 1996–2012. *J. Clean. Prod.* 102, 103–114. <https://doi.org/10.1016/j.jclepro.2015.04.037>.
- Luca, D., Rodriguez-Pose, A., 2019. Building consensus: shifting strategies in the territorial targeting of Turkey's public transport investment. *Reg. Stud.* 53 (11), 1591–1602. <https://doi.org/10.1080/00343404.2019.1594750>.
- Ma, J., Liu, Z., Chai, Y., 2015. The impact of urban form on CO₂ emission from work and non-work trips: the case of Beijing, China. *Habitat Int.* 47, 1–10. <https://doi.org/10.1016/j.habitatint.2014.12.007>.
- Ma, J., Ye, X., Pinjari, A.R., 2019. Practical method to simulate multiple discrete-continuous generalized extreme value model: application to examine substitution patterns of household transportation expenditures. *Transport. Res. Rec.* 1–12. <https://doi.org/10.1177/0361198119842819>.
- MFA, 2023. Republic of Turkiye ministry of foreign affairs. <https://www.mfa.gov.tr/kuresel-isinma-bm-iklim-degisikligi-cerceve-sozlesmesi-ve-kyo-protokolu.tr.mfa>. (Accessed 21 October 2023).
- Miao, L., Gu, H., Zhang, X., Chen, W., Wang, M., 2019. Factors causing regional differences in China's residential CO₂ emissions—evidence from provincial data. *J. Clean. Prod.* 224, 852–863. <https://doi.org/10.1016/j.jclepro.2019.03.271>.
- Mokhtarian, P.L., 2009. If telecommunication is such a good substitute for travel, why does congestion continue to get worse? *Transportation Letters* 1 (1), 1–17. <https://doi.org/10.3328/TL.2009.01.01.1-17>.
- Mokhtarian, P.L., Tal, G., 2013. Impacts of ICT on travel behavior: a tapestry of relationships. *The SAGE Handbook of Transport Studies* 14, 241–260. Washington, DC: Sage.
- Moran, D., Wood, R., Hertwich, E., et al., 2020. Quantifying the potential for consumer-oriented policy to reduce European and foreign carbon emissions. *Clim. Pol.* 20, S28–S38. <https://doi.org/10.1080/14693062.2018.1551186>.
- ODMD, 2023. Automotive Distributors and Mobility Association. (Accessed 1 October 2023).
- OECD, 2021. Carbon Pricing in Times of COVID-19: what Has Changed in G20 Economies? OECD, Paris. <https://www.oecd.org/tax/tax-policy/carbon-pricing-in-times-of-covid-19-what-has-changed-in-g20-economies.htm>.
- Olvera, L.D., Plat, D., Pochet, P., 2008. Household transport expenditure in Sub-Saharan African cities: measurement and analysis. *J. Transport Geogr.* 16 (1), 1–13. <https://doi.org/10.1016/j.jtrangeo.2007.04.001>.
- Pichler, P.P., Zwicker, T., Chavez, A., Kretschmer, T., Seddon, J., Weisz, H., 2017. Reducing urban greenhouse gas footprints. *Sci. Rep.* 7, 14659. <https://doi.org/10.1038/s41598-017-15303-x>.
- Pudney, S., 1989. Modelling Individual Choice. Basil Blackwell, Oxford. <https://www.ssc.wisc.edu/~walker/wp-content/uploads/2013/09/pudney89chapter2.pdf>.
- Saz-Salazar, S.D., Rausell-Köster, P., 2008. A Double-Hurdle model of urban green areas valuation: dealing with zero responses. *Landsc. Urban Plann.* 84 (3–4), 241–251. <https://doi.org/10.1016/j.landurbplan.2007.08.008>.
- Sharif, A., Raza, S.A., Ozturk, I., Afshan, S., 2019. The dynamic relationship of renewable and nonrenewable energy consumption with carbon emission: a global study with the application of heterogeneous panel estimations. *Renew. Energy* 133, 685–691. <https://doi.org/10.1016/j.renene.2018.10.052>.
- Sheraz, M., Deyi, X., Ahmed, J., Ullah, S., Ullah, A., 2021. Moderating the effect of globalization on financial development, energy consumption, human capital, and carbon emissions: evidence from G20 countries. *Environ. Sci. Pollut. Control Ser.* 28, 35126–35144. <https://doi.org/10.1007/s11356-021-13116-0>.
- Soleymani, S., 2019. CO₂ emissions patterns in 7 top carbon emitter economies: the case of transport sector. *Energy* 168, 989–1001. <https://doi.org/10.1016/j.energy.2018.11.145>.
- Soltani, M., Rahmani, O., Ghasimi, D.S., et al., 2020. Impact of household demographic characteristics on energy conservation and carbon dioxide emission: case from Mahabad city, Iran. *Energy* 194, 116916. <https://doi.org/10.1016/j.energy.2020.116916>.

- STATISTA, 2022. Transportation emissions worldwide - statistics &facts. <https://www.statista.com/topics/7476/transportation-emissionsworldwide/#dossierContentsoutinerWrapper>. (Accessed 15 June 2022).
- Tian, X.L., An, C.J., Chen, Z.K., 2020. Assessing the impact of urban form on the greenhouse gas emissions from household vehicles: a review. *J. Environ. Inform. Lett.* 3, 70–85. <https://doi.org/10.3808/jeil.202000029>.
- TSI, Turkish Statistical Institute, 2023. Ankara, Turkiye. <https://data.tuik.gov.tr/Bulletin/Index?p=Motorlu-Kara-Tasitlari-Haziran-2023-49427>. (Accessed 1 October 2023).
- Vuong, Q.H., 1989. Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica: J. Econom. Soc.* 57 (2), 307–333. <https://doi.org/10.2307/1912557>.
- Wang, Z., Liu, W., 2014. The impacts of individual behavior on household daily travel carbon emissions in Beijing, China. *Energy Proc.* 61, 1318–1322. <https://doi.org/10.1016/j.egypro.2014.11.1090>.
- Wang, Z., Cui, C., Peng, S., 2019. How do urbanization and consumption patterns affect carbon emissions in China? A decomposition analysis. *J. Clean. Prod.* 211, 1201–1208. <https://doi.org/10.1016/j.jclepro.2018.11.272>.
- Wiedenhofer, D., Smetschka, B., Akenji, L., Jalas, M., Haberl, H., 2018. Household time use, carbon footprints, and urban form: a review of the potential contributions of everyday living to the 1.5 °C climate target. *Curr. Opin. Environ. Sustain.* 30, 7–17. <https://doi.org/10.1016/j.cosust.2018.02.007>.
- Xie, J., Zhou, S., Teng, F., Gu, A., 2023. The characteristics and driving factors of household CO₂ and non-CO₂ emissions in China. *Ecol. Econ.* 213, 107952 <https://doi.org/10.1016/j.ecolecon.2023.107952>.
- Xu, B., Lin, B., 2015. Factors affecting carbon dioxide (CO₂) emissions in China's transport sector: a dynamic nonparametric additive regression model. *J. Clean. Prod.* 101, 311–322. <https://doi.org/10.1016/j.jclepro.2015.03.088>.
- Yang, W., Li, T., Cao, X., 2015. Examining the impacts of socio-economic factors, urban form and transportation development on CO₂ emissions from transportation in China: a panel data analysis of China's provinces. *Habitat Int.* 49, 212–220. <https://doi.org/10.1016/j.habitatint.2015.05.030>.
- Yang, Y., Wang, C., Liu, W., 2018. Urban daily travel carbon emissions accounting and mitigation potential analysis using surveyed individual data. *J. Clean. Prod.* 192, 821–834. <https://doi.org/10.1016/j.jclepro.2018.05.025>.
- Zahabi, S.A.H., Miranda-Moreno, L., Patterson, Z., Barla, P., Harding, C., 2012. Transportation greenhouse gas emissions and its relationship with urban form, transit accessibility and emerging green technologies: A Montreal case study. *Procedia-Social and Behavioral Sciences* 54, 966–978. <https://doi.org/10.1016/j.sbspro.2012.09.812>.
- Zhang, H., Shi, X., Cheong, T., Wang, K., 2020. Convergence of carbon emissions at the household level in China: a distribution dynamics approach. *Energy Econ.* 10 <https://doi.org/10.1016/j.eneco.2020.104956>.
- Zhao, P., Bai, Y., 2019. The gap between and determinants of growth in car ownership in urban and rural areas of China: a longitudinal data case study. *J. Transport Geogr.* 79, 102487 <https://doi.org/10.1016/j.jtrangeo.2019.102487>.
- Zhu, Z., Liu, Y., Tian, X., Wang, Y., Zhang, Y., 2017. CO₂ emissions from the industrialization and urbanization processes in the manufacturing center Tianjin in China. *J. Clean. Prod.* 168, 867–875. <https://doi.org/10.1016/j.jclepro.2017.08.245>.