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The gasoline price and the commuting behavior of US commuters: Exploring changes to green travel mode choices

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A B S T R A C T

This paper explores how gasoline prices and the commuting behavior of US commuters are related, with a focus on the use of private motor vehicles, public transit, walking, and cycling. Basic economic theory suggests that as gasoline prices rise, there tends to be a decrease in the consumption of gasoline due to the substitution and income effect, leading to a reduced use of private motor vehicles by commuters who may opt for relatively cheaper modes of transportation for their daily commutes. Using data from the American Time Use Survey spanning from 2003 to 2019, coupled with state- and year-specific gasoline prices, the study reveals a positive relationship between gasoline prices and daily commuting time. Furthermore, gasoline prices are also associated with the choice of commuting modes. Higher gasoline prices are negatively related to the proportion of commuting time using private motor vehicles and positively related to the proportion of commuting time using public transit, walking, and cycling. Heterogeneity analysis reveals that the association between gasoline prices and the proportion of commuting time using public transit and walking varies depending on the rural status of commuters. The results of this paper can be used to formulate pricing policies in order to change the daily travel choices of commuters, mitigate greenhouse gas emissions, and develop a less fuel-dependent transport sector in the US.

1. Introduction

Commuting is a daily activity for millions of workers and has been increasing in distance and duration in many countries. Consequently, commuting poses significant environmental challenges due to its contribution to greenhouse gas (GHG) emissions, particularly in developed countries, where the majority of commuting is done by private car. For example, approximately 90 % of all US workers commute to their workplaces using passenger cars (Wener and Evans, 2011; Gimenez-Nadal and Molina, 2019; Echeverría et al., 2022). This heavy reliance on private cars makes them a major contributor to GHG emissions, necessitating the identification of factors driving car usage rather than green alternatives such as public transit, walking, or cycling. Promoting sustainable and inclusive development, and aiming to decarbonize daily mobility, is crucial to understanding the forces influencing commuting choices (UNFCCC, 2015, 2016).

Although changing travel behavior can be challenging, an in-depth analysis of mode choice in urban mobility can lay the foundation for policies that encourage a shift towards less carbon-intensive travel options. Public transit and active mobility modes, like walking or cycling, are recognized as "zero carbon" alternatives for personal mobility. Encouraging the use of physically active modes of transportation in commuting not only helps reduce carbon emissions but also holds the potential to improve the health of commuters (Tajalli and Hajbabaie, 2017; Jacob et al., 2021).

How individuals commute to/from work is a personal choice and there are many factors influencing this choice (Woodcock et al., 2009; Páez and Whalen, 2010; Popuri et al., 2011; Wener and Evans, 2011; Olsson et al., 2013), so it would be useful for planners to know consumer responses to changes in energy prices, a variable which they can target through pricing measures. The basic economic theory of consumer demand indicates an inverse correlation between gasoline prices and car usage, and a positive correlation with alternative commuting modes like walking and cycling. This is because the costs associated with driving may rise as gasoline prices increase. The substitution effect entails a reduction in the proportion of time spent in private motor vehicles,

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which rely on gasoline, and an increase in alternative modes of transportation such as public transit or active commuting. Conversely, the income effect results in a decrease in household disposable income due to higher gasoline prices, potentially prompting more physical activity for commuting and reducing the reliance on private motor vehicles and public transit, both of which involve monetary expenditure.

Prior research has examined consumer responses to changes in carbon taxes (Davis and Kilian, 2011; Li et al., 2014; Gimenez-Nadal and Molina, 2019), although the evidence points towards consumers responding differentially to changes in taxes and changes in prices (Davis and Kilian, 2011; Li et al., 2014; Rivers and Schaufele, 2017; Kilian and Zhou, 2024). Hence, quantifying the association between fuel price and commuting behavior, and specifically the mode choice for commuting trips, is critical for public policy. If an increase in the gasoline price could make commuters substitute driving for more physically demanding modes of transport that are zero carbon-emitting modes (active transport), pricing policies could be a viable solution for reducing car use and fossil-fuel dependence.

We explore the relationship between daily commuting time, commuting mode choices, and gasoline prices in the United States. Utilizing data spanning from 2003 to 2019 sourced from the American Time Use Survey (ATUS) and gasoline prices data from the U.S. Energy Information Administration (EIA), we delve into the intricate relationship between these variables. The ATUS, a comprehensive time-use survey, provides diary-based data wherein participants meticulously log their daily activities, along with pertinent details such as location, mode of transportation, and companionship during said activities. Extensive research has underscored the reliability and efficacy of diary-based data compared to other methodologies like stylized questionnaires (Bonke, 2005; Kan, 2008), establishing it as the gold standard for time-use research (Aguiar and Hurst, 2007; Guryan et al., 2008). Leveraging this rich dataset enables us to dissect daily commuting time comprehensively, including factors like walking to transit, making it a more nuanced analysis than what is typically derived from the National Household Travel Survey (NHTS).

Our findings indicate a positive relationship between gasoline prices and the total time spent commuting per day. Specifically, a 1 % rise in gasoline prices is positively related to a 0.278 % increase in daily commuting time, all else being equal. Furthermore, we observe significant positive relationships between gasoline prices and the proportion of commuting time allocated to green travel modes, such as public transit, walking, and cycling, juxtaposed with a negative association with the proportion of commuting time spent in private motor vehicles. Quantitatively, a 1 % increase in gasoline prices is associated with a 0.207 percentage point decrease in the proportion of commuting time by private motor vehicles, along with increases of 0.073, 0.090, and 0.044 percentage points in the proportion of commuting time by public transit, walking, and cycling, respectively, while holding other variables constant. Overall, the results suggest that commuters adjust their driving behavior by opting for cheaper and slower modes of transportation for their work commutes. All these results can be used to predict public transport and other ridership trends when fuel prices change.

We further investigate whether the results vary based on the urban/rural status of commuters, revealing significant differences in the estimated relationships between daily commuting time, travel modes, and gasoline prices. Specifically, as gasoline prices rise, urban commuters exhibit a more notable transition towards utilizing public transit, while rural commuters significantly augment their reliance on walking for commuting purposes and barely modify their proportion of commuting time done by public transit. Disparities in transportation infrastructure, accessibility to alternative modes of transportation, and the types of job opportunities available may elucidate these variations in the associations between gasoline prices and commuting behavior. In urban areas, public transportation networks are often more developed than in rural areas. As gasoline prices rise, urban commuters may find it easier to switch to public transit compared to rural commuters. In contrast, rural areas may have less robust public transit options, offering fewer alternatives to driving such as active forms. Consequently, higher gasoline prices may prompt a shift to walking and cycling as an alternative to driving in rural areas.

The contribution of the paper revolves around three key aspects. Firstly, we investigate the relationship between gasoline prices and daily commuting time. Previous studies have predominantly focused on metrics such as distance traveled or gasoline consumption. However, our research uniquely explores the significance of commuting time—a variable that offers valuable insights not captured by conventional measures of travel distance, including factors like traffic density, accessibility, and mode choice.

Secondly, we analyze the association between gasoline prices and travel mode selection for commuting, with a specific focus on evaluating the trade-offs associated with mode switching in response to fluctuations in gasoline prices. To the best of our knowledge, our study marks the first comprehensive evaluation of this relationship, distinguishing itself from prior analyses that primarily concentrated on specific transportation modes, notably automobile usage, thereby overlooking other green modes such as public transit and active travel. In particular, the temporal structure of the ATUS allows us to accurately quantify the time dedicated to commuting per day and discern the specific modes of transportation employed, including activities like walking to transit. Moreover, unlike the NHTS, which is conducted every eight years, the ATUS has been conducted annually since January 2003 across the United States. This continuous data collection ensures that our findings are less susceptible to being influenced by transient economic conditions or specific stages of the business cycle (e.g., a period of stable gasoline prices in the latter wave of 2017 NHTS vs. a period of high gasoline prices in the prior wave of 2009 NHTS).

Finally, we examine the relationship between gasoline prices and commuting, paying attention to the geographical context of commuters' residences. Our analysis reveals that the results differ depending on the urban/rural status of commuters. All these findings highlight the importance of pricing in the adoption of energy-efficient travel modes and emphasize the critical role of gasoline prices in reducing carbon emissions.

The rest of the paper is organized as follows. Section 2 surveys the related literature. Section 3 presents the ATUS data, the sample, and the variables used in the analysis, and Section 4 describes the econometric strategy. Section 5 dicusses the main empirical results, and Section 6 addresses the policy implications. Finally, Section 7 concludes.

2. Literature review

The commuting behavior of workers has become a topic of special interest in recent research. This may be due to the significant effects associated with daily commuting with regard to aspects such as time allocation, subjective well-being, traffic congestion, traffic accidents, and pollutant emissions, among others. Furthermore, commuting time accounts for a significant proportion of daily life due to its compulsory nature, especially for those workers who have a full-time job and cannot work from home, and several authors have pointed out that this time-consuming activity has increased in importance in many developed economies (Susilo and Maat, 2007; Kirby and LeSage, 2009; Gimenez-Nadal et al., 2018, 2022b).

How individuals respond to changes in gasoline prices has been a longstanding topic of interest among economists and there is a large literature that explicitly focuses on the relationship between gasoline prices and several observable driving behaviors, such as driving distance, gasoline consumption, traffic congestion issues or new vehicles registered. In this context, several gasoline price elasticities of demand have been reported for distinct time horizons and countries (see Labandeira et al. (2017) and Dimitropoulos et al. (2018) for two recent meta-analysis of energy price elasticities of demand). The evidence points to a decline in the short-run gasoline price elasticity of demand by the early 2000s in the US, a period of relatively stable and low gasoline prices (Small and Van Dender, 2007; Hughes et al., 2008; Hymel et al., 2010), whereas other studies point to a statistically significant jump in the short-run gasoline price elasticity of demand through the 2010s in the US (Lin and Prince, 2013; Hymel and Small, 2015; Goetzke and Vance, 2021), suggesting that the gasoline price elasticity of demand is ultimately time-variant.

Other studies have focused on the relationship between gasoline prices and the use of specific modes of transport (DeLoach and Tiemann, 2012; Iseki and Ali, 2014; Nguyen and Pojani, 2024) or traffic flows (Zhang and Burke, 2020; Pang et al., 2023). DeLoach and Tiemann (2012) find that a 1 % increase in gasoline prices correlates with a 0.502 percentage point rise in the proportion of shared driving among friends and colleagues. Similarly, Iseki and Ali (2014) estimate a bus ridership elasticity of 0.061 in the US. More recently, Nguyen and Pojani (2024) show that Vietnamese commuters exhibit high sensitivity to fluctuations in fuel costs, prompting shifts in their transportation modes from motorcycles to bicycles. In terms of traffic dynamics, Zhang and Burke (2020) observe an elasticity of traffic flows to gasoline prices equal to −0.04 in Australia, whereas Pang et al. (2023) identify a traffic congestion elasticity concerning gasoline prices at −0.087 in China.

Increasing research attention has been paid to fuel price elasticities of driving in other geographical contexts beyond the US (Alberini et al., 2022; Ahmed et al., 2023; Tilov and Weber, 2023). For instance, Tilov and Weber (2023) document a short-run fuel price elasticity ranging from −0.6 to −0.8 for vehicle miles traveled (VMT) in Switzerland, a relatively high fuel price elasticity in comparison to earlier estimates. For other time horizons, Gillingham (2014) estimates a medium-run elasticity of VMT to the gasoline price of −0.22 in California, and Gillingham and Munk-Nielsen (2019) estimate a medium-run elasticity of VMT to fuel price of −0.30 in Denmark. Finally, Severen and van Benthem (2022) find that those who lived through the oil crises of the 1970s at the ages of 15–18 are less inclined to use a private motor vehicle for commuting and significantly reduce their use of private motor vehicles for travel to work three decades later. All this suggests that the impact of fuel prices on driving behaviors may take time to manifest.

3. Data and variables

We use data from the 2003–2019 American Time Use Survey (ATUS), a cross-sectional database, to analyze the commuting behavior of US workers. The ATUS is conducted by the US Census Bureau and sponsored by the Bureau of Labor Statistics (BLS) and is considered the official time use survey of the US. It provides information on individual time use, where respondents are asked to fill out in their own words a diary summarizing episodes of the prior day. The surveys are in English and Spanish, and are primarily conducted by telephone, although special provision is made to contact those who are impossible to reach by phone.

The ATUS asks one person over age 15 per household, randomly chosen, who has successfully completed the Current Population Survey (CPS) 2–5 months before, to sequentially describe their activities during a 24-h period (from 4:00 a.m. to 4:00 a.m. of the next day) preceding the day of the interview (the “diary day”). For each episode, the ATUS collects the start and stop times, and thus we can add up the time spent participating in any given reference activity (e.g., paid work, leisure, childcare, market work, commuting, personal care, housework).

Given the substantial impact of the COVID-19 pandemic on workers' commuting behaviors, with the rise of hybrid work and remote working arrangements, we have chosen not to incorporate data from the additional survey waves for 2020, 2021, and 2022 in this article. We have alternatively focused on data spanning from 2003 to 2022, as detailed in Table A1 in Appendix A, where we estimate a participation model. In this model, the dependent variable indicates whether workers allocate positive amounts of time to commuting (coded as 1) or not (coded as 0). Notably, the dummy variable representing the post-COVID period (2020−2022) yields a coefficient of −0.151, statistically significant at the 1 % level. This suggests a notable shift in commuting patterns during these years, likely attributed to COVID-19 restrictions and the proliferation of hybrid work and remote work practices (Barrero et al., 2023).

We restrict the sample to individuals who commute during the diary day, excluding teleworkers and those who work from home (van Ommeren and van der Straaten, 2008; Gimenez-Nadal et al., 2018, 2024), and who have completed their diaries on working days. Working days are defined as days where individuals spend at least 60 min on market work activities, excluding commuting. Additionally, we exclude self-employed workers, as previous research indicates significant differences in commuting behaviors among them (van Ommeren and van der Straaten, 2008; Gimenez-Nadal et al., 2018, 2020, 2024; Albert et al., 2019). Individuals with missing information on the variables we use are also excluded. The analysis is conducted at the individual level, resulting in a sample size of 47,343 commuters.

From the time use diary of the survey we define the (log) commuting time in minutes per day, and the percentage of commuting time done by various modes of transport per day. We define the daily commuting time variable as the sum of all episodes of commuting reported by each worker throughout the diary day. For the percentage of commuting time by the various modes of transport, the ATUS includes information about the following modes of transport: ‘car, truck, or motorcycle (as driver or passenger)’, ‘walking’, ‘bus’, ‘subway/train’, ‘bicycle’, ‘boat/ferry’, ‘taxi/limousine service’, and ‘airplane’. From these, we create the following groupings: private motor vehicle (car, truck, or motorcycle, both as driver or passenger), public transit (bus, subway/train, boat/ferry, taxi/limousine service, or airplane), walking, and cycling (bicycle). We calculate and distinguish the proportions of commuting time by private motor vehicle, public transit, walking, and cycling, defined as the daily time devoted to commuting using the reference mode of transport, divided by the total time in commuting per day.

One constraint of these surveys is the absence of data on commuting distance, despite the availability of comprehensive activity-level information. However, the time and distance of commuting exhibit a strong correlation (Roberts et al., 2011; Dickerson et al., 2014), and commuting time provides valuable insights for transportation policymaking and planning that are not addressed by alternative data sources. Time, being a scarce resource, plays a pivotal role in understanding individual well-being and economic outcomes. Recent evidence indicates a rise in average commuting time across several countries (Gimenez-Nadal et al., 2018, 2022b), suggesting that commuting may impede other beneficial uses of time such as socialization, exercise, or relaxation (Kahneman et al., 2004; Kahneman and Krueger, 2006), potentially hampering worker productivity (van Ommeren and Gutiérrez-i-Puigarnau, 2011; Gibson and Shrader, 2018; Ma and Ye, 2019; Gimenez-Nadal et al., 2022a), given its repetitive and obligatory nature. Additionally, commuting time provides better insights into traffic patterns and congestion issues, including accidents, traffic accessibility, density, mode choice, and speed, which are not adequately captured by alternative sources like commuting distance or kilometers traveled to work.

The primary explanatory variable in our study is the gasoline price, sourced from the U.S. Energy Information Administration (EIA). The EIA offers comprehensive historical time series data on annual energy prices across major economic sectors for all 50 states and the District of Columbia. These prices represent retail gasoline prices and encompass both federal and state motor fuel taxes. However, it is important to note that they do not include state general sales taxes, local fuel taxes, or local sales taxes due to non-uniformity in their application. These prices are presented in current dollars per million British thermal units (Btus) by the EIA to facilitate comparison across different energy sources. To align with our analysis, we convert the original prices from dollars per million Btus to dollars per gallon of automotive gasoline. Furthermore, to ensure consistency and facilitate meaningful comparisons over time, the final price series are adjusted for inflation to constant 2015 dollars using the US consumer price index.

Utilizing individual data gathered from the ATUS, we also examine various socio-demographic and geographic characteristics of commuters that have been identified as correlated with commuting time. These variables aim to capture the diversity among commuters, whether at the individual or household level. Initially, we consider the gender of commuters, defining a binary variable where 1 represents male and 0 represents female. Additionally, we include the respondent's age as a continuous variable measured in years at the time of the interview. It is hypothesized that individuals with higher educational attainment may dedicate more time to commuting, as they typically earn higher wages enabling longer travel distances. To address this hypothesis, we introduce controls for the maximum level of education attained by respondents. Specifically, we define three dummy variables: one for primary education, one for secondary education, and one for university education. Primary education denotes individuals without a high school diploma, secondary education signifies high school graduates, and university education indicates individuals with education beyond high school (e.g., some college and more). Since full-time workers are more likely to commute and can commute for longer due to lower opportunity costs of time, we also define a binary variable where 1 indicates full-time workers and 0 indicates others.

Lastly, we include controls for observed household heterogeneity among respondents. Specifically, we incorporate controls for marital status using a binary variable: 1 indicates the presence of a partner, whether married or cohabiting, in the household, while 0 indicates otherwise. Additionally, we account for the labor force status of the respondent's partner with a binary variable: 1 denotes employment status of the partner, and 0 denotes otherwise. Furthermore, we consider the number of children in the household. For this, we control for the total count of children under 18 in the household and introduce two dummy variables indicating the presence of children aged between 0 and 5 and between 6 and 17, respectively. Recognizing the association between higher income and longer commutes, we explicitly adjust for household total income. This information is provided by the ATUS in income ranges, and we categorize household total income into three brackets: ‘Low income’ (<$25,000), ‘Medium income’ ($25,000–$75,000), and ‘High income’ (>$75,000).

Table 1 presents the descriptive statistics of our variables. On average, commuters in the sample spend 43 min per day commuting. The predominant mode of commuting is private motor vehicle, constituting over 94 % of the total commuting time per day. Public transit accounts for only 2.4 % of daily commuting time, walking for 2.9 %, and cycling for 0.6 %. The average gasoline price in our sample, spanning from 2003 to 2019, is $2.92 per gallon (expressed in 2015 dollars), with a standard deviation of approximately $0.59 per gallon. Men comprise slightly over half of the sample (around 54 %), with the average age of commuters being approximately 40 years old. Regarding educational attainment, 9.6 % of commuters have primary education, 28.1 % have completed secondary education, and 62.3 % have pursued at least some college education. Furthermore, 83.7 % of commuters are employed full-time.

In terms of household composition, more than half of the sample live as a couple, with around 61 % of commuters residing with a partner. Additionally, 45.6 % report having a partner who works, and the average number of children under 18 in the sample is 0.8. Approximately 18 and 25 % of commuters have children under the age of 6 or between the ages of 6 and 17, respectively. Moreover, in terms of household income, 13.3 % of households in the sample have an income of less than $25,000, 46.9 % fall within the $25,000–$75,000 income bracket, and 39.8 % earn more than $75,000.

The ATUS provides data on the geographical location of respondents, which has been identified as a determinant of commuting behavior (Manaugh et al., 2010; Sandow and Westin, 2010; Dargay and Clark, 2012; Zhu et al., 2019; Gimenez-Nadal et al., 2020, 2022b). It is plausible that commuters may react differently to fluctuations in gasoline prices based on their residential location, given the known disparities in infrastructure provision across regions (Li et al., 2021; Echeverría et al., 2022; Tilov and Weber, 2023). Consequently, the dynamics of price associations could vary. For instance, in urban areas, a rise in gasoline prices might prompt a shift from private motor vehicle usage to public transit due to the greater availability of transit options. However, in rural areas where such infrastructure is lacking, commuters may face limited alternatives for adjusting their commuting modes. In this context, the ATUS also includes data on the metropolitan status of respondents' locations. We utilize this information to create a binary variable: 1 indicates the commuter resides in a rural area (‘Nonmetropolitan’), while a 0 denotes an urban area (‘Metropolitan, central city’, ‘Metropolitan, balance of MSA’, ‘Metropolitan not identified’).

Table 1
Summary statistics.

	Mean	Std. Dev.	Units of measurement
Dependent variable:			
Commuting time	43.172	37.792	Minutes per day
Percentage of commuting by private motor vehicle	94.113	22.447	Percentage
Percentage of commuting by public transit	2.395	14.073	Percentage
Percentage of commuting walking	2.891	14.931	Percentage
Percentage of commuting cycling	0.600	7.598	Percentage
Variable of interest:			
Gasoline price	2.920	0.591	Dollars per gallon (2015$)
Socio-demographics/controls:			
Being male	54.042	49.837	Percentage
Age	40.183	13.604	Years old
Primary education	9.583	29.435	Percentage
Secondary education	28.139	44.968	Percentage
University education	62.278	48.470	Percentage
Full-time worker	83.690	36.946	Percentage
Having a partner	60.821	48.815	Percentage
Partner works	45.626	49.809	Percentage
Number of children <18	0.801	1.114	Continuous variable
Children aged 0–5	18.057	38.466	Percentage
Children aged 6–17	24.955	43.276	Percentage
Low household income (< $25,000)	13.264	33.919	Percentage
Medium household income ($25,000 - $75,000)	46.888	49.904	Percentage
High household income (> $75,000)	39.848	48.959	Percentage

Notes: Summary statistics computed using sample weights included in the survey. Sample is restricted to commuters who spend more than 60 min in market work activities excluding commuting. Self-employed workers are excluded from the analysis.

Table 2 shows the average time devoted to commuting per day and the percentage of commuting time done by modes of transport, for both urban and rural areas, along with p-values for the differences between urban and rural areas (based on a t-type test of the equality of sample means). There are large differences between urban and rural areas in relation to commuting. Among commuters in urban areas, the average commuting time is 44 min per day, and the percentage of commuting time by private motor vehicle, public transit, walking, and cycling is 93.58, 2.76, 3.05, and 0.62 %, respectively. For rural areas, the average commuting time is 36 min per day, and the percentage of commuting time by private motor vehicle, public modes, walking, and bicycle is 97.02, 0.40, 2.04, and 0.54 %, respectively.

Significant differences between urban and rural areas in terms of commuting behavior and the percentage of commuting time by various modes of transportation, notably private motor vehicles, public transit, and walking, are evident at standard levels (p-values below 0.001). Our analysis reveals that commuters in urban areas spend an additional 8.1 min per day commuting, constituting approximately 22 % of total commuting time, compared to their rural counterparts. Moreover, the percentage of commuting done by private motor vehicle is 3.45 percentage points lower among urban commuters. Conversely, commuters in urban areas exhibit higher percentages of commuting by public transit

Table 2
Summary statistics, urban area.

	Urban		Rural			
	Mean	Std. Dev.	Mean	Std. Dev.	Difference	*p*-value
Commuting time	44.448	37.585	36.347	38.139	8.100***	(<0.001)
Percentage of commuting by private motor vehicle	93.576	23.386	97.022	16.168	−3.446***	(<0.001)
Percentage of commuting by public transit	2.761	15.067	0.397	5.998	2.363***	(<0.001)
Percentage of commuting walking	3.046	15.203	2.043	13.270	1.003 ***	(<0.001)
Percentage of commuting cycling	0.617	7.689	0.537	7.264	0.079	(0.414)
Gasoline price	2.927	0.591	2.885	0.596	0.042***	(<0.001)
Observations	39,525		7450			

Notes: Summary statistics computed using sample weights included in the survey. Sample is restricted to commuters who spend more than 60 min in market work activities excluding commuting. Self-employed workers are excluded from the analysis. Differences calculated as the mean values in urban areas minus the mean values in rural areas. *p*-value of the difference in parentheses.

and walking, with increases by 2.36 and 1 percentage points, respectively. However, the disparities in commuting by bicycle between urban and rural areas are not statistically significant at standard levels. The results may reveal differences in commuting behavior between commuters residing in rural and urban areas. Further exploration of these disparities will be conducted later in the paper.

4. Econometric strategy

We now explain the methodology applied to achieve the results. First, we analyze the relationship between daily commuting time and travel mode choices, on the one hand, and gasoline price, on the other, controlling for other factors that may be relevant for the dependent variable and correlated with the gasoline price, such as observable characteristics of commuters, and time or seasonal effects. Later, we explore whether these relationships differ according to the urban status of the commuters' residence, as it is quite likely that commuters in rural areas have limited access to public transit services.

To analyze the time allocated to commuting per day, we employ linear regression models utilizing Ordinary Least Squares (OLS). Specifically, we estimate the following linear equation at the individual level to examine the association between gasoline prices and daily commuting time, while controlling for variances in observable socio-demographic and household characteristics of commuters or time effects:

$$log(C_{it}) = \alpha + \beta log\left(GasPrice_{jt}\right) + \gamma X_{it} + \delta Year_{it} + \theta Month_{it} + \varphi Day_{it} + \varepsilon_{it} \tag{1}$$

where C_{it} represents the daily minutes commuter "*i*" in year "*t*" devotes to commuting, $GasPrice_{jt}$ is the gasoline price of state "*j*" in time "*t*", X_{it} denotes a vector of socio-demographic/control characteristics of commuter "*i*" in time "*t*", and ε_{it} is the regression error term that captures unmeasured variables and measurement errors. Thus, the gasoline price coefficient, i.e., the coefficient of interest, is identified by cross-state variations over time. We transform the dependent variable of daily commuting time and the gasoline price to their logarithm form in order to interpret the estimated coefficient as an elasticity (i.e., the percentage change in daily commuting time associated with a 1 % increase in the gasoline price, keeping other variables constant). We also include several vectors of variables measuring time ($Year_{it}$, $Month_{it}$, Day_{it}). $Year_{it}$ is a vector of year dummy variables (category of reference: 2019), $Month_{it}$ is a vector of month-of-year dummy variables (category of reference: December), and Day_{it} is a vector of day-of-week dummy variables (category of reference: Sunday), reflecting the day of the interview of commuter "*i*". Thus, reference diaries refer to Sundays of December 2019. We include these fixed effects to partially capture differences between days, months, and years (i.e., to control for cyclical dimensions that may affect both commuting time and the gasoline price).

The vector X_{it} includes various characteristics of commuters that may be correlated with commuting time and may be biasing estimates of the relationship between gasoline price and commuting time. These variables are the gender of the respondent (1 if male), age (measured in years) and its quadratic form, maximum level of education achieved (ref.: primary education), full-time status (1 if a full-time worker), whether the respondent is cohabiting (1 if yes), the partner's employment status (1 if partner works), the number of children, the presence of children under age 6 and between 6 and 17 in the household, and the household income (ref.: low household income or less than $25,000). Estimates include robust standard errors clustered at the state-year level to account for potential heteroskedasticity and a potential relationship between gas prices and cost of living, and observations are weighted at the individual-level using demographic survey weights.

We also analyze the relationship between the proportion of commuting time done by private motor vehicle, public transit, walking, and cycling, on the one hand, and gasoline price, on the other. To that end, we jointly estimate the following linear equations, where the dependent variables are the proportion of commuting time done by each transport mode, in a seemingly unrelated regression (SUR) framework:

$$P_{it} = \alpha + \beta log\left(GasPrice_{jt}\right) + \gamma X_{it} + \delta Year_{it} + \theta Month_{it} + \varphi Day_{it} + \varepsilon_{it} \tag{2}$$

where P_{it} denotes the proportion of commuting time done by either car, public transit, walking, or cycling by commuter "*i*" at time "*t*", and the rest of the specification remains analogous to Eq. (1). We adopt a simultaneous equation modeling approach through SUR to estimate the parameters of Eq. (2), and account for the dependence among the four mode choices (i.e., the sum of the proportion of commuting of all travel modes must always be one in our sample). Similar to Eq. (1), the coefficient of interest in Eq. (2) is β, which indicates the percentage point alteration in the proportion of commuting time attributed to each mode of transport corresponding to a 1 % rise in gasoline price, holding all other factors constant. Since the dependent variables in Eq. (2) pertain to commuting shares and are quantified in proportion terms (ranging from 0 to 1), the estimations of β can be directly understood as the percentage point shift in the proportion of commuting time facilitated by a particular mode of transport linked with a 1 % increase in gasoline price, while other variables remain unchanged.

In a further analysis, we investigate whether the associations between gasoline prices, daily commuting and mode choices vary based on the spatial characteristics of the commuters' residential areas. To do so, we introduce a dummy variable representing the rural status of the geographical residence of commuters, which takes a value of 1 if the commuter resides in a rural area, and 0 if the commuter resides in an urban area. This dummy variable of rural area is fully interacted with all explanatory variables included in Eqs. (1) and (2). Consequently, we augment Eqs. (1) and (2) and employ a fully interacted model for the (log) commuting time per day, and four simultaneous models fully interacted for the proportion of commuting time attributed to private motor vehicle, public transit, walking, and cycling, respectively.

5. Results

5.1. Main results

Table 3 presents the results of estimating Eqs. (1) and (2) for the relationship between daily commuting time and travel modes, on the one hand, and gasoline prices, on the other. We observe that an increase in gasoline price is negatively related to the proportion of commuting time via private motor vehicles, while it is positively related to the proportion of commuting time via public transit, walking, and cycling. Ultimately, rising gasoline costs may positively impact daily commuting times due to the predominance of slower transportation modes, such as public transit or active forms of travel, when gasoline prices are higher, thereby prolonging daily commuting duration.

In Column (1), we observe a positive relationship between gasoline price and commuting time, implying that a 1 % rise in gasoline price corresponds to a 0.278 % increase in total commuting time per day, a statistically significant relationship at the 1 % level, all else being equal. This elasticity is quite similar, in absolute terms, to previous elasticities of VMT in the US, which range between −0.3 and − 0.2 (see Goetzke and Vance (2021) for a recent overview). This similarity is remarkable but not surprising given the correlation between travel time and VMT. Specifically, our estimated elasticity translates to an additional 0.12 min of commuting per day, on average, when the gasoline price increases by 1 %.

Taking into account the average values displayed in Table 1 and converting this elasticity to a marginal effect in levels (i.e., multiplying the elasticity by the ratio of average daily commuting time to gasoline prices), we can also calculate the revealed opportunity cost of commuting adjusted to an hourly rate. This represents the value of time spent commuting per day that could have been used for other activities. From a back-of-the-envelope calculation, the opportunity cost of time would be approximately $14.6 per hour. This reflects the potential benefits lost due to time spent commuting per day (see Appendix B for a summary of the procedure and a comparison with the average wage rate).

Columns (2) to (5) present the findings regarding the proportion of commuting time distributed among various modes of transportation. Notably, the share of commuting time spent in private motor vehicle is negatively related to gasoline price, whereas the proportion of commuting time undertaken through green travel modes (such as public transit, walking, and cycling) is positively related to gasoline price. Specifically, a 1 % increase in the gasoline price is related to a decrease of 0.207 percentage points in the proportion of commuting time done by car, while it is positively related to an increase of 0.073, 0.090, and 0.044 percentage points in the proportion of commuting time using public transit, walking, and cycling, respectively, holding other variables constant. These shifts equate to a reduction of 0.08937 min in car commuting time per day and increases of 0.03152, 0.03885, and 0.01899 min in daily commuting time for public transit, walking, and cycling, respectively, keeping other variables constant.

Regarding socio-demographic characteristics, being male is associated with more time devoted to commuting per day, and the daily commuting times of males are on average 19.006 % greater than their

Table 3
Main estimates.

	(1)	(2)	(3)	(4)	(5)
	log(Commuting)	Proportion by car	Proportion by public transit	Proportion walking	Proportion cycling
Log of gasoline price	0.278***	−0.207***	0.073***	0.090***	0.044***
	(0.085)	(0.037)	(0.022)	(0.019)	(0.009)
Being male	0.174***	−0.011***	−0.001	0.007***	0.005***
	(0.011)	(0.003)	(0.002)	(0.002)	(0.001)
Age	0.022***	−0.001*	0.001***	0.000	−0.000
	(0.003)	(0.001)	(0.001)	(0.000)	(0.000)
Age squared/100	−0.024***	0.002***	−0.002***	−0.001	0.000
	(0.003)	(0.001)	(0.001)	(0.001)	(0.000)
Secondary education	−0.081***	0.024***	−0.014***	−0.006	−0.003*
	(0.019)	(0.006)	(0.004)	(0.004)	(0.002)
University education	−0.016	0.004	−0.005	0.001	0.000
	(0.018)	(0.005)	(0.004)	(0.004)	(0.002)
Full-time worker	0.188***	0.025***	−0.004	−0.020***	−0.001
	(0.016)	(0.005)	(0.003)	(0.003)	(0.002)
Having a partner	0.136***	0.023***	−0.010***	−0.014***	0.001
	(0.017)	(0.005)	(0.003)	(0.003)	(0.001)
Partner works	−0.124***	0.003	−0.005**	0.004*	−0.001
	(0.016)	(0.004)	(0.002)	(0.002)	(0.001)
Number of children <18	−0.012	−0.004	0.001	0.002	0.000
	(0.009)	(0.003)	(0.002)	(0.001)	(0.001)
Children aged 0–5	−0.040*	0.027***	−0.006	−0.016***	−0.004*
	(0.022)	(0.006)	(0.005)	(0.004)	(0.002)
Children aged 6–17	−0.020	0.026***	−0.010**	−0.012***	−0.004**
	(0.019)	(0.005)	(0.004)	(0.003)	(0.002)
Medium household income ($25,000 - $75,000)	0.049***	0.038***	−0.007***	−0.025***	−0.006**
	(0.016)	(0.005)	(0.003)	(0.004)	(0.003)
High household income (> $75,000)	0.163***	0.036***	−0.003	−0.026***	−0.007***
	(0.018)	(0.006)	(0.003)	(0.004)	(0.003)
Constant	2.344***	1.064***	−0.034	−0.004	−0.026***
	(0.102)	(0.037)	(0.023)	(0.020)	(0.008)
Weekday F.E.	Yes	Yes	Yes	Yes	Yes
Month-of-year F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
Observations	47,343	47,343	47,343	47,343	47,343
R-squared	0.049	0.021	0.008	0.015	0.007

Notes: The ATUS (2003–2019) has been restricted to commuters on their working days. Self-employed workers are excluded from the analysis. Estimates are weighted using demographic survey weights. Robust standard errors, clustered at the state-year level, reported in parentheses. R-squared value denotes the explanatory power of all independent variables, including the explanatory power of the fixed effects. The omitted weekday, month-of-year and year dummies are Sunday, December, and 2019, respectively. * Significant at the 10 % level, ** significant at the 5 % level, *** significant at the 1 % level.

female counterparts. Among males, larger proportions of commuting time are done walking and by bicycle, which are around 0.7 and 0.5 percentage points higher, while a negative relationship is found with the proportion of commuting time by car and the proportion of commuting time by car is 1.1 percentage points lower for males. For age, we find an inverted U-shaped association with commuting time and the proportion of commuting time done by public transit. The maximum daily commuting time and proportion of commuting time by public transit is reached at the ages of 45 and 25, respectively.

We also find a negative relationship between secondary education and daily commuting time, in comparison to those with primary education. Having achieved secondary education is associated with a decrease of 7.781 % in daily commuting time, compared to those with primary education. Secondary education is also negatively related to the proportion of commuting time by public transit, and cycling, with these relationships ranging from −1.4 to −0.3 percentage points, whereas those commuters who have achieved secondary education do a larger proportion of their commuting by private car, and the proportion of commuting time by car is 2.4 percentage points greater, in comparison to those with primary education. Furthermore, the relationship between the full-time status of workers and total commuting time per day is positive and statistically significant at standard confidence levels, indicating that full-time workers commute for longer per day than do part-time employees; on average, their commuting times are 20.683 % greater per day. We also observe a positive relationship between being a full-time worker and the proportion of commuting time by private motor vehicle, which is above 2.5 percentage points, whereas full-time work is negatively related to the proportion of commuting time spent walking, with this relationship being about −2 percentage points.

Household composition appears to be significantly correlated with daily commuting time and the proportion of commuting time done by modes of transport. We observe that when commuters have a partner, their time devoted to commuting is 14.568 % greater per day, and a larger proportion, about 2.3 percentage points, of their commuting is done by private motor vehicle, compared to public transit and walking, which are negatively related to cohabiting. The estimates suggest that, for those cohabiting, their proportions of commuting time done by public transit and walking are 1 and 1.4 percentage points lower, respectively. Additionally, those in a working couple devote 11.662 % less minutes to commuting per day and their proportion of commuting time by public transit is 0.5 percentage points lower, in comparison to those who do not have a partner who works.

The presence of children under 5 years old is associated with a greater proportion of commuting time by car, which is around 2.7 percentage points higher, whereas the proportion of commuting time by public transit of those commuters with children under 5 years old in the household is 1.6 percentage points lower. The presence of children aged 6–17 is negatively associated with the proportion of commuting time done by public transit, walking and cycling, and positively related to the proportion of commuting time by car. Thus, those commuters with children aged 6–17 years old show a shift from green travel modes to private car. Specifically, the estimates suggest that the proportion of commuting time done by car is 2.6 percentage points greater for those commuters with children aged between 6 and 17, whereas their proportion of commuting time done by public transit, walking and cycling is 1, 1.2 and 0.4 percentage points lower, respectively.

Household income is positively related to daily commuting time and the proportion of commuting time by private car, while it is negatively associated with the proportion of commuting time by green alternatives. Thus, for higher-income households, there is a substitution from green forms of commuting to private car, suggesting that those with higher incomes tend to choose modes of transport that are more expensive, such as the car. The estimates document that those commuters who have a household income between $25,000 and $75,000 devote 5.022 % more minutes to commuting per day, whereas those commuters who have a household total income above $75,000 devote 17.704 % more minutes to daily commuting than low-income households. Besides, those commuters who have a medium or high household income also display greater proportions of commuting times by car, of about 3.8 and 3.6 percentage points more, respectively. For the proportion of commuting time by public transport, the results indicate that commuters in households with medium earnings have 0.7 percentage points lower use of public transit, whereas their proportion of commuting time done walking and cycling are 2.5 and 0.6 percentage points lower, respectively, in comparison to households with low household income. Finally, commuters with high household income have a lower proportion of commuting time done walking and cycling—approximately 2.6 and 0.7 percentage points lower, respectively—than those with low household income.

It is worth noting that the models exhibit limited fitting, with R-squared values varying between 0.007 and 0.049, despite the addition of multiple control covariates that previous research, as well as this study, has identified as relevant to daily commutes. This implies that a significant portion of daily commutes and travel choices remains unexplained. Nevertheless, we must keep in mind that these limited predictive abilities are standard in commuting research, indicating the influence of unobservable or stochastic factors in commuting behaviors (Gimenez-Nadal and Molina, 2019; Gimenez-Nadal et al., 2018, 2020).

5.2. Heterogeneity analysis

We now analyze whether the relationship between gasoline price and daily commuting behavior varies based on the location of commuters, which is crucial for evaluating the effectiveness of pricing policies. Table 2 shows that daily commuting time and the percentages of commuting time by different transport modes, together with the gasoline price, vary according to the urban status of the area of residence. Table 4 shows the results of estimating Eqs. (1) and (2) fully interacted with a dummy variable indicating rural areas, according to the commuter's urban residence status. (The variation in the sample size is because of missing information about metropolitan areas in 368 respondents).

We observe differential associations between gasoline price and commuting mode choice according to the urban/rural residence of commuters, as expected. Increases in gasoline prices relate to a more noticeable increase in public transit in urban areas, while rural commuters show a more pronounced transition towards walking and hardly modify their time spent on public transit for daily commuting, compared to their counterparts. However, for other transportation modes examined, namely private motor vehicle and cycling, no statistically significant differences are found in the relationship between gasoline prices and the proportion of commuting time spent via these modes between urban and rural areas, as the interaction between the gasoline price and the dummy variable for rural areas is statistically not significant in these regressions. This suggests that the extent to which an increase of 1 % in the gasoline price is associated with the proportion of commuting time done by car and cycling is similar in these two areas.

In terms of magnitudes, Column (1) of Table 4 shows that the gasoline price is positively related to the daily commuting time, and an increase of 1 % in gasoline prices is associated with a 0.20 % increase in daily commuting time, statistically significant at the 5 % level, holding other variables constant. This suggests an increase of 0.086 min spent commuting per day. Besides, the interaction term between the gasoline price and rural area equals −0.177, which practically cancels out the relationship between the gasoline price and daily commuting time. However, this estimate does not display statistically significant values at standard levels, and the *p* value for the test of significance for the interaction term is 0.599, so the relationship between gasoline price and daily commuting time does not differ between urban and rural areas. Finally, we also find that those in rural areas spent more minutes per day on commuting than their urban counterparts.

For travel mode choices in Columns (2–5), a 1 % rise in the gasoline

Table 4
Heterogeneity analysis, urban area.

	(1)	(2)	(3)	(4)	(5)
	log(Commuting)	Proportion by car	Proportion by public transit	Proportion walking	Proportion cycling
Log of gasoline price	0.200**	−0.191***	0.069***	0.078***	0.045***
	(0.081)	(0.039)	(0.025)	(0.018)	(0.009)
Log of gasoline price X Rural area	−0.177	−0.069	−0.055**	0.131**	−0.008
	(0.336)	(0.063)	(0.027)	(0.054)	(0.021)
Rural area	0.669**	0.075	0.047	−0.128**	0.006
	(0.338)	(0.064)	(0.030)	(0.050)	(0.024)
Weekday F.E.	Yes	Yes	Yes	Yes	Yes
Month-of-year F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
All controls, interactions and constant	Yes	Yes	Yes	Yes	Yes
Observations	46,975	46,975	46,975	46,975	46,975
R-squared	0.062	0.025	0.012	0.017	0.009

Notes: The ATUS (2003–2019) has been restricted to commuters on their working days. Self-employed workers are excluded from the analysis. Estimates are weighted using demographic survey weights. Robust standard errors, clustered at the state-year level, reported in parentheses. R-squared value denotes the explanatory power of all independent variables, including the explanatory power of the fixed effects. The omitted weekday, month-of-year and year dummies are Sunday, December, and 2019, respectively. * Significant at the 10 % level, ** significant at the 5 % level, *** significant at the 1 % level.

price is related to a decrease of 0.191 percentage points in the proportion of commuting time done by private motor vehicle, all else being equal. Besides, this decrease of 0.08246 min in daily car commuting time is similar for rural and urban areas, since the interaction term between the log of gasoline price and rural area is not statistically significant at standard levels ($p = 0.275$). On the other hand, an increase of 1 % in the gasoline price is positively related to an increase of 0.045 percentage points in the proportion of commuting time done cycling, keeping other variables constant. When testing whether there is any difference in this estimate across urban and rural areas, we find that the interaction term for the log of gasoline price and rural area is not statistically significant at standard levels ($p = 0.719$). Hence, we observe a similar increase of 0.01943 min in daily commuting time by bicycle related to an increase of 1 % in the gasoline price in both urban and rural areas, holding other variables constant.

Conversely, statistically significant differences emerge in the relationship between the proportion of commuting time done by public transit or walking, on the one hand, and gasoline prices, on the other, according to the geographical location of commuters. In particular, an increase of 1 % in the gasoline price is related to a higher increase in the proportion of commuting time by public transit in urban areas, compared to rural areas where the proportion of commuting time by public transit is nearly inelastic with respect to gasoline prices. Alternatively, a 1 % rise in the gasoline price is associated with a larger increase in the proportion of commuting time spent walking in rural areas compared to urban areas. In terms of magnitude, an increase of 1 % in gasoline prices is positively related to a 0.069 percentage point increase in the proportion of commuting time done by public transit in urban areas, whereas it is associated with a 0.014 percentage point increase in rural areas, all else equal. This difference corresponds to 0.02375 more minutes of commuting time by public transit in urban areas per day when gasoline prices increase by 1 % and is statistically significant at the 5 % level ($p = 0.042$). For the proportion of commuting done walking, a 1 % rise in gasoline prices is positively related to an increase of 0.078 percentage points in urban areas, whereas in rural areas it is related to an increase of 0.209 percentage points in the proportion of commuting done walking, keeping other variables constant. This suggests a raw difference of 0.05655 additional minutes in daily commuting time by walking in rural areas in comparison to urban areas when gasoline prices increase by 1 %, with this difference being highly significant ($p = 0.015$).

5.3. Probability of choosing green transport options

Our main approach involves estimating two different specifications, focusing on the daily commuting time and the proportion of commuting time done by private motor vehicles, public transit, walking, and cycling. However, an additional margin through which gasoline prices may impact daily commuters' behavior is by changing the number of commuters using specific modes, besides modifying the time devoted to such travel choices per day.

To check this margin, we alternatively analyze the probability of using specific modes. We estimate four different linear probability models through OLS where the dependent variables take the value of 1 if the commuter devotes positive amounts of time to daily commuting by either car, public transit, walking, or cycling, and 0 otherwise. We also consider an additional dependent variable that takes the value of 1 if the commuter takes a green travel option, and 0 otherwise. Table 5 presents the main estimates (additional coefficients are available upon request).

Estimates from Panel A show that a 1 % rise in the gasoline price relates to a 0.171 percentage point decrease in the probability of using a car for daily commutes. Conversely, an increase of 1 % in the gasoline price is positively related to increases of 0.094, 0.201, and 0.049 percentage points in the probability of using public transit, walking, or cycling, respectively, for daily commuting, holding other variables constant. Overall, a 1 % increase in the gasoline price is associated with a 0.288 percentage point increase in the probability of choosing a green travel mode for daily commuting, all else being equal. These results are consistent with those displayed in Table 3 and suggest that higher gasoline prices lead to more commuters using green travel modes and more time spent using these modes for daily commutes. However, only a minority of commuters use a green transport option in the US (i.e., about 3633 commuters in our sample) and can make a switch from car to green travel mode choices. In terms of magnitude and scaled by the average, the increase for the number of commuters who use a green travel mode choice is about 3.6 percentage points when gasoline prices rise by 1 %. According to the disaggregation by modes of transport, the increases range from 3.03 percentage points for public transit to 7 percentage points for bicycles.

Panel B of Table 5 presents the estimates for five fully interacted linear probability models and suggests that an increase of 1 % in gasoline prices relates to a higher increase in the probability of using public transit in urban areas compared to rural areas. Numerically, an increase of 1 % in the gasoline price is associated with a 0.089 percentage point increase in the probability of using public transit in urban areas, compared to a 0.017 percentage point increase in rural areas. Additionally, this difference of 0.072 percentage points in the probability of using public transit when gasoline prices rise by 1 % between urban and rural areas is statistically significant at the 5 % level ($p = 0.026$). Hence, it appears that fewer commuters can switch to public transit in rural areas than in urban areas when gasoline prices rise, a result fully consistent with the estimates of Table 4. Additional rural interactions do

Table 5
Participation estimates.

	(1)	(2)	(3)	(4)	(5)
	Prob(Car)	Prob (Public transit)	Prob (Walking)	Prob (Cycling)	Prob (Green)
Panel A. Main estimates					
Log of gasoline price	−0.171***	0.094***	0.201***	0.049***	0.288***
	(0.035)	(0.027)	(0.031)	(0.009)	(0.039)
Weekday F.E.	Yes	Yes	Yes	Yes	Yes
Month-of-year F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
All controls and constant	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	0.953	0.031	0.059	0.007	0.080
Observations	47,343	47,343	47,343	47,343	47,343
R-squared	0.022	0.009	0.013	0.007	0.019
Panel B. Full interaction estimates					
Log of gasoline price	−0.162***	0.089***	0.180***	0.050***	0.265***
	(0.037)	(0.031)	(0.034)	(0.009)	(0.042)
Log of gasoline price X Rural area	−0.020	−0.072**	0.145*	−0.013	0.112
	(0.058)	(0.032)	(0.081)	(0.021)	(0.084)
Rural area	0.039	0.053	−0.147*	0.013	−0.113
	(0.059)	(0.035)	(0.080)	(0.025)	(0.086)
Weekday F.E.	Yes	Yes	Yes	Yes	Yes
Month-of-year F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
All controls, interactions and constant	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	0.953	0.031	0.059	0.007	0.080
Observations	46,975	46,975	46,975	46,975	46,975
R-squared	0.026	0.013	0.016	0.009	0.022

Notes: OLS estimates. The ATUS (2003–2019) has been restricted to commuters on their working days. Self-employed workers are excluded from the analysis. Estimates are weighted using demographic survey weights. Robust standard errors, clustered at the state-year level, reported in parentheses. R-squared value denotes the explanatory power of all independent variables, including the explanatory power of the fixed effects. The omitted weekday, month-of-year and year dummies are Sunday, December, and 2019, respectively. * Significant at the 10 % level, ** significant at the 5 % level, *** significant at the 1 % level.

not display statistically significant values ($p > 0.05$).

5.4. Robustness checks

We perform a battery of robustness checks to show the sensitivity of our main findings in Table 3, with Table 6 reporting the main coefficient of interest. Since part-time workers are expected to have different characteristics in the relationship between gasoline price and commuting from those of full-time workers, Panel A of Table 6 displays the results of omitting part-time workers. Furthermore, in Panel B we additionally control for the occupation characteristics of commuters by accounting for 22 different occupation categories available from the ATUS (with farming, fishing, and forestry occupations serving as the reference category), so the estimates are net for observed occupation differences among commuters. Finally, Panel C displays the results when we include self-employed workers, together with an indicator to control for those workers (4823 workers are self-employed in this sample). The results remain unchanged for all robustness checks. (Additional coefficients are shown in Tables A2, A3, and A4 in Appendix A).

We further investigate the robustness of our findings by employing alternative estimation methods. Specifically, we utilize Poisson and negative binomial estimators, which are designed to handle instances of zeros in the dependent variables, including zero-commuters on the diary day. Remarkably, the outcomes derived from these alternative methods closely align with the conclusions drawn from our primary estimates presented in Column (1) of Table 3 and are available upon request.

6. Policy discussion

The findings from this study have significant policy implications that can guide the development of transportation policies aimed at reducing carbon emissions and promoting green travel mode choices. By analyzing a comprehensive micro-dataset over an extended time frame representing the entire US population, the research underscores the importance of understanding the link between gasoline prices, daily commuting time, and travel modes. The study reveals that higher gasoline prices are associated with longer daily commuting times. This is primarily because commuters shift their preferences from faster transportation modes, such as private cars, to slower alternatives like public transit, walking, or cycling. Consequently, rising gasoline prices are positively related to an increased predominance of greener transportation options for commuting purposes, with more commuters using green travel modes and dedicating additional time to such options each day, ultimately increasing the observed daily commuting times.

These results suggest that price-based measures, such as fuel or carbon taxes, could be effective instruments for influencing commuter behavior, reducing driving, and curbing greenhouse gas emissions from the transportation sector. However, these measures would also impose greater time burdens due to the increased reliance on green travel modes. Transportation planners should not overlook this trade-off between time pressures for commuters and environmental benefits. Nevertheless, the generally low elasticity estimates pose a significant barrier to change, a finding consistent with previous estimates using other metrics for driving behavior (Goetzke and Vance, 2021).

A common concern regarding the implementation of pricing policies is their distributive effects across different areas; such policies disproportionately affect those living outside urban areas. The economic rationale is that rural areas, compared to urban areas, have limited public transport infrastructure, giving rural commuters fewer viable transport alternatives when gasoline prices fluctuate. This may impact public acceptance of such policies, as evidenced by the yellow vest demonstrations in France. Our heterogeneity analysis considers these geographical differences and finds that the extent of mode switching varies based on the geographical setting of commuters.

Specifically, we find that commuters in urban areas show a more pronounced shift towards public transit when gasoline prices rise, compared to their rural counterparts. In contrast, commuters in rural areas increase the proportion of their commuting time spent walking and cycling but hardly change their use of public transit. Hence, our estimates are influenced by the availability of public transport networks in urban areas, while rural commuters exhibit more rigid behavior, adapting their transportation modes mainly by increasing the time spent walking and cycling. This result emphasizes the need for tailored policy measures, rather than a one-size-fits-all approach, to address regional differences in response to gasoline price fluctuations, garner political support, and achieve environmental benefits.

Table 6
Robustness checks.

	(1)	(2)	(3)	(4)	(5)
	log(Commuting)	Proportion by car	Proportion by public transit	Proportion walking	Proportion cycling
Panel A. Omitting part-time workers					
Log of gasoline price	0.301***	−0.207***	0.080***	0.084***	0.043***
	(0.092)	(0.038)	(0.023)	(0.018)	(0.011)
Weekday F.E.	Yes	Yes	Yes	Yes	Yes
Month-of-year F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
Observations	39,771	39,771	39,771	39,771	39,771
R-squared	0.035	0.020	0.009	0.010	0.008
Panel B. Including occupation characteristics					
Log of gasoline price	0.299***	−0.202***	0.071***	0.088***	0.042***
	(0.085)	(0.036)	(0.022)	(0.018)	(0.009)
Weekday F.E.	Yes	Yes	Yes	Yes	Yes
Month-of-year F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
Occupation F.E.	Yes	Yes	Yes	Yes	Yes
Observations	47,343	47,343	47,343	47,343	47,343
R-squared	0.064	0.032	0.016	0.019	0.011
Panel C. Including self-employed workers					
Log of gasoline price	0.287***	−0.208***	0.076***	0.089***	0.044***
	(0.087)	(0.036)	(0.021)	(0.019)	(0.008)
Weekday F.E.	Yes	Yes	Yes	Yes	Yes
Month-of-year F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
Observations	52,166	52,166	52,166	52,166	52,166
R-squared	0.045	0.021	0.009	0.014	0.007

Notes: The ATUS (2003–2019) has been restricted to commuters on their working days. Self-employed workers are excluded from the analysis. Panel A excludes part-time workers. Panel B controls for worker characteristics, with the omitted category being Farming, fishing, and forestry occupations. Panel C includes self-employed workers, together with an indicator for self-employed workers. Estimates are weighted using demographic survey weights. Robust standard errors, clustered at the state-year level, reported in parentheses. R-squared value denotes the explanatory power of all independent variables, including the explanatory power of the fixed effects. The omitted weekday, month-of-year and year dummies are Sunday, December, and 2019, respectively. * Significant at the 10 % level, ** significant at the 5 % level, *** significant at the 1 % level.

7. Conclusions

This paper analyzes how gasoline price relates to commuters' daily travel time and mode choice. To that end, we use data from the American Time Use Survey for the period 2003–2019 and compute the total commuting time per day, and the proportion of commuting time done by private motor vehicle, public transit, walking, and cycling. The results suggest that the gasoline price is positively related to the total commuting time per day. Besides, the gasoline price is positively related to the proportion of commuting time done by public transit and active modes (walking and cycling), while it is negatively related to the proportion of commuting time by private modes (car, truck, or motorcycle, both as driver or passenger). The results for the probability of using such modes are similar. Consequently, commuters adapt their driving behavior when gasoline prices are higher by shifting from private motor vehicle towards cheaper and slower modes of transport.

Differences in transportation infrastructure across areas may influence our overall results. We additionally consider the geographical setting of commuters' residence and obtain similar associations between gasoline prices and the proportion of commuting time using private modes and cycling in urban and rural areas. However, we report differential associations between gasoline prices, on the one hand, and the proportion of commuting time by public transit and walking, on the other, based on whether commuters reside in urban or rural areas. The results indicate that increases in gasoline prices are related to a noticeable increase in public transit in urban areas. In contrast, rural commuters show little change in their use of public transport and display a more pronounced shift towards walking for daily commuting, compared to their counterparts. Consequently, commuters in rural areas have fewer transportation alternatives to driving, resulting in more rigid commuting behaviors.

The analysis from this paper is not without limitations. A key limitation lies in the nature of our data, which consists of cross-sectional samples of individuals. Consequently, the respondents differ across survey years. Therefore, our results should be interpreted as conditional correlations, rather than causal, and we are unable to isolate the effect of gasoline prices from permanent individual heterogeneity in preferences. Furthermore, the regression analysis assumes directional causality from independent to dependent variables, but the potential endogeneity of certain variables (e.g., education, household income) may lead to biased estimates, limiting the ability to establish a definitive causal relationship. Similarly, it is widely acknowledged that there exists substantial variability in gasoline prices within a single state, underscoring the need for forthcoming studies to employ more granular data on gasoline prices, such as metrics at the county or city level.

A promising avenue for future research would be to expand the analysis to encompass additional travel categories, in order to test the applicability of our results. The structure of the ATUS dataset enables such an exploration. We demonstrate here that the gasoline prices influence daily commuting behavior and may similarly impact other trip purposes such as housework, leisure, childcare, or personal care travel. Nevertheless, such trips are discretionary and represent a smaller portion of time. An additional aspect worth investigating is the relationship between gasoline prices and telework, given that encouraging commuters to work remotely could result in fewer vehicles on the road and a consequent decrease in carbon emissions, ultimately benefiting the environment. Finally, the economic welfare effects are not included in the analysis, and we propose this as a direction for future research for a more comprehensive understanding of the implications of pricing policies.

CRediT authorship contribution statement

Ignacio Belloc: Writing – original draft, Investigation, Formal analysis, Data curation, Conceptualization. **José Ignacio Gimenez-Nadal:** Writing – review & editing, Validation, Supervision, Project

administration, Methodology, Investigation, Funding acquisition, Conceptualization. **José Alberto Molina:** Writing – review & editing, Resources, Project administration, Investigation, Funding acquisition, Conceptualization.

Data availability

Data will be made available on request.

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Declaration of competing interest

None.

Appendix A. Additional results

Table A1
Participation in daily commuting estimates.

	(1)
	Participation in daily commuting
Dummy if year ≥2020	−0.151***
	(0.010)
Being male	0.010**
	(0.004)
Age	0.006***
	(0.001)
Age squared/100	−0.008***
	(0.001)
Secondary education	0.045***
	(0.008)
University education	−0.033***
	(0.008)
Full-time worker	0.131***
	(0.006)
Having a partner	0.022***
	(0.006)
Partner works	−0.003
	(0.006)
Number of children <18	−0.001
	(0.003)
Children aged 0–5	−0.016**
	(0.008)
Children aged 6–17	−0.020***
	(0.007)
Medium household income ($25,000–$75,000)	−0.007
	(0.006)
High household income (>$75,000)	−0.062***
	(0.007)
Constant	0.396***
	(0.023)
Weekday F.E.	Yes
Month-of-year F.E.	Yes
Year F.E.	Yes
Observations	75,605
R-squared	0.089

Notes: The ATUS (2003−2022) has been restricted to workers on their working days. Self-employed workers are excluded from the analysis. Estimates are weighted using demographic survey weights. Robust standard errors reported in parenteheses. R-squared value denotes the explanatory power of all independent variables, including the explanatory power of the fixed effects. The omitted weekday, month-of-year and year dummies are Sunday, December, and 2019, respectively. * Significant at the 10 % level, ** significant at the 5 % level, *** significant at the 1 % level.

Table A2
Main estimates excluding part-time workers.

	(1)	(2)	(3)	(4)	(5)
	log(Commuting)	Proportion by car	Proportion by public transit	Proportion walking	Proportion cycling
Log of gasoline price	0.301***	−0.207***	0.080***	0.084***	0.043***
	(0.092)	(0.038)	(0.023)	(0.018)	(0.011)
Being male	0.178***	−0.008***	−0.001	0.004**	0.004***

(*continued on next page*)

Table A2 (*continued*)

	(1)	(2)	(3)	(4)	(5)
	log(Commuting)	Proportion by car	Proportion by public transit	Proportion walking	Proportion cycling
	(0.012)	(0.003)	(0.002)	(0.002)	(0.001)
Age	0.015***	−0.000	0.000	0.000	−0.000
	(0.003)	(0.001)	(0.001)	(0.000)	(0.000)
Age squared/100	−0.017***	0.001	−0.001	−0.001	0.000
	(0.004)	(0.001)	(0.001)	(0.000)	(0.000)
Secondary education	−0.092***	0.017***	−0.010***	−0.004	−0.002
	(0.024)	(0.006)	(0.004)	(0.004)	(0.002)
University education	−0.033	−0.005	0.000	0.003	0.002
	(0.023)	(0.005)	(0.003)	(0.004)	(0.002)
Having a partner	0.148***	0.020***	−0.009***	−0.011***	0.000
	(0.018)	(0.005)	(0.003)	(0.003)	(0.001)
Partner works	−0.130***	0.006	−0.007***	0.002	−0.001
	(0.017)	(0.004)	(0.002)	(0.002)	(0.001)
Number of children <18	−0.005	0.001	−0.001	0.000	−0.000
	(0.010)	(0.002)	(0.002)	(0.001)	(0.001)
Children aged 0–5	−0.070***	0.018***	−0.003	−0.011***	−0.004*
	(0.024)	(0.006)	(0.005)	(0.003)	(0.002)
Children aged 6–17	−0.017	0.017***	−0.004	−0.009***	−0.004**
	(0.021)	(0.005)	(0.004)	(0.003)	(0.002)
Medium household income ($25,000–$75,000)	0.067***	0.033***	−0.007**	−0.021***	−0.006*
	(0.020)	(0.006)	(0.003)	(0.004)	(0.003)
High household income (>$75,000)	0.200***	0.027***	0.001	−0.021***	−0.006*
	(0.022)	(0.007)	(0.004)	(0.004)	(0.003)
Constant	2.595***	1.069***	−0.022	−0.021	−0.026***
	(0.116)	(0.036)	(0.024)	(0.018)	(0.009)
Weekday F.E.	Yes	Yes	Yes	Yes	Yes
Month-of-year F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
Observations	39,771	39,771	39,771	39,771	39,771
R-squared	0.035	0.020	0.009	0.010	0.008

Notes: The ATUS (2003–2019) has been restricted to commuters on their working days. Self-employed and part-time workers are excluded from the analysis. Estimates are weighted using demographic survey weights. Robust standard errors reported in parentheses. R-squared value denotes the explanatory power of all independent variables, including the explanatory power of the fixed effects. The omitted weekday, month-of-year and year dummies are Sunday, December, and 2019, respectively. * Significant at the 10 % level, ** significant at the 5 % level, *** significant at the 1 % level.

Table A3
Main estimates accounting for occupation characteristics.

	(1)	(2)	(3)	(4)	(5)
	log(Commuting)	Proportion by car	Proportion by public transit	Proportion walking	Proportion cycling
Log of gasoline price	0.299***	−0.202***	0.071***	0.088***	0.042***
	(0.085)	(0.036)	(0.022)	(0.018)	(0.009)
Being male	0.138***	−0.017***	0.003	0.009***	0.005***
	(0.013)	(0.003)	(0.002)	(0.002)	(0.001)
Age	0.019***	−0.002**	0.001***	0.000	−0.000
	(0.003)	(0.001)	(0.001)	(0.000)	(0.000)
Age squared/100	−0.021***	0.002***	−0.002***	−0.001	−0.000
	(0.003)	(0.001)	(0.001)	(0.001)	(0.000)
Secondary education	−0.081***	0.023***	−0.014***	−0.006	−0.002
	(0.019)	(0.006)	(0.004)	(0.004)	(0.002)
University education	−0.015	0.015**	−0.011**	−0.004	0.000
	(0.019)	(0.006)	(0.004)	(0.004)	(0.002)
Full-time worker	0.159***	0.023***	−0.003	−0.020***	−0.000
	(0.016)	(0.005)	(0.003)	(0.004)	(0.002)
Having a partner	0.126***	0.023***	−0.009***	−0.015***	0.001
	(0.017)	(0.005)	(0.003)	(0.003)	(0.001)
Partner works	−0.114***	0.002	−0.005**	0.004*	−0.002
	(0.016)	(0.004)	(0.002)	(0.002)	(0.001)
Number of children <18	−0.010	−0.003	0.001	0.002	0.000
	(0.009)	(0.002)	(0.002)	(0.001)	(0.001)
Children aged 0–5	−0.048**	0.026***	−0.006	−0.016***	−0.004*
	(0.022)	(0.006)	(0.005)	(0.003)	(0.002)
Children aged 6–17	−0.020	0.025***	−0.010**	−0.011***	−0.004*
	(0.019)	(0.005)	(0.004)	(0.003)	(0.002)
Medium household income ($25,000–$75,000)	0.042***	0.037***	−0.007**	−0.025***	−0.005**
	(0.016)	(0.005)	(0.003)	(0.004)	(0.002)
High household income (>$75,000)	0.143***	0.041***	−0.005	−0.029***	−0.007***
	(0.018)	(0.006)	(0.003)	(0.004)	(0.003)
Constant	2.341***	1.097***	−0.060**	−0.011	−0.027**
	(0.116)	(0.037)	(0.024)	(0.022)	(0.011)
Weekday F.E.	Yes	Yes	Yes	Yes	Yes

(*continued on next page*)

Table A3 (*continued*)

	(1)	(2)	(3)	(4)	(5)
	log(Commuting)	Proportion by car	Proportion by public transit	Proportion walking	Proportion cycling
Month-of-year F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
Occupation F.E.	Yes	Yes	Yes	Yes	Yes
Observations	47,343	47,343	47,343	47,343	47,343
R-squared	0.064	0.032	0.016	0.019	0.011

Notes: The ATUS (2003–2019) has been restricted to commuters on their working days. Self-employed workers are excluded from the analysis. Estimates are weighted using demographic survey weights. Robust standard errors reported in parentheses. R-squared value denotes the explanatory power of all independent variables, including the explanatory power of the fixed effects. The omitted weekday, month-of-year, year and occupation dummies are Sunday, December 2019, and Farming, fishing, and forestry occupations, respectively. * Significant at the 10 % level, ** significant at the 5 % level, *** significant at the 1 % level.

Table A4
Main estimates including self-employed workers.

	(1)	(2)	(3)	(4)	(5)
	log(Commuting)	Proportion by car	Proportion by public transit	Proportion walking	Proportion cycling
Log of gasoline price	0.287***	−0.208***	0.076***	0.089***	0.044***
	(0.087)	(0.036)	(0.021)	(0.019)	(0.008)
Self-employed worker	−0.058***	0.011***	−0.007***	−0.002	−0.002
	(0.019)	(0.004)	(0.002)	(0.003)	(0.001)
Being male	0.181***	−0.010***	−0.001	0.007***	0.005***
	(0.010)	(0.003)	(0.002)	(0.002)	(0.001)
Age	0.022***	−0.001*	0.001***	0.000	−0.000
	(0.003)	(0.001)	(0.000)	(0.000)	(0.000)
Age squared/100	−0.025***	0.002***	−0.002***	−0.000	0.000
	(0.003)	(0.001)	(0.000)	(0.000)	(0.000)
Secondary education	−0.091***	0.026***	−0.015***	−0.007*	−0.004**
	(0.019)	(0.006)	(0.004)	(0.004)	(0.002)
University education	−0.026	0.007	−0.006*	−0.000	−0.001
	(0.018)	(0.005)	(0.004)	(0.004)	(0.002)
Full-time worker	0.166***	0.024***	−0.004	−0.019***	−0.001
	(0.015)	(0.004)	(0.003)	(0.003)	(0.002)
Having a partner	0.125***	0.023***	−0.010***	−0.014***	0.000
	(0.016)	(0.005)	(0.003)	(0.003)	(0.001)
Partner works	−0.117***	0.003	−0.005**	0.004	−0.001
	(0.015)	(0.003)	(0.002)	(0.002)	(0.001)
Number of children <18	−0.012	−0.003	0.001	0.002	−0.000
	(0.009)	(0.002)	(0.002)	(0.001)	(0.001)
Children aged 0–5	−0.034	0.025***	−0.004	−0.017***	−0.004*
	(0.022)	(0.006)	(0.005)	(0.003)	(0.002)
Children aged 6–17	−0.022	0.024***	−0.009**	−0.012***	−0.003
	(0.019)	(0.005)	(0.004)	(0.003)	(0.002)
Medium household income ($25,000–$75,000)	0.035**	0.035***	−0.007***	−0.023***	−0.005**
	(0.016)	(0.005)	(0.003)	(0.004)	(0.002)
High household income (>$75,000)	0.140***	0.034***	−0.004	−0.024***	−0.006**
	(0.018)	(0.006)	(0.003)	(0.004)	(0.002)
Constant	2.361***	1.061***	−0.032	−0.003	−0.026***
	(0.106)	(0.036)	(0.022)	(0.020)	(0.007)
Weekday F.E.	Yes	Yes	Yes	Yes	Yes
Month-of-year F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
Observations	52,166	52,166	52,166	52,166	52,166
R-squared	0.045	0.021	0.009	0.014	0.007

Notes: The ATUS (2003–2019) has been restricted to commuters on their working days. Estimates are weighted using demographic survey weights. Robust standard errors reported in parentheses. R-squared value denotes the explanatory power of all independent variables, including the explanatory power of the fixed effects. The omitted weekday, month-of-year and year dummies are Sunday, December, and 2019, respectively. * Significant at the 10 % level, ** significant at the 5 % level, *** significant at the 1 % level.

Appendix B. Opportunity cost of time

To calculate the opportunity cost of time (OCT) from our estimates, we draw on data from Tables 1 and 3 and perform a back-of-the-envelope calculation. In Column (1) of Table 3, we estimate a log-log model where we regress the log of daily commuting time on the log of gasoline price, as expressed in Eq. (1):

$$log(C_{it}) = \alpha + \beta log\left(GasPrice_{jt}\right) + \gamma X_{it} + \delta Year_{it} + \theta Month_{it} + \varphi Day_{it} + \varepsilon_{it} \tag{1}$$

From the regression equation, where the specification employs the logarithms of both daily commuting time and gasoline prices, β can be interpreted as the elasticity of daily commuting time with respect to gasoline prices:

$$\beta = \frac{\partial log(C)}{\partial log(GasPrice)} \tag{2}$$

In Table 3, we find that $\beta = 0.278$, indicating that a 1 % increase in gasoline prices is positively related to a 0.278 % increase in the time devoted to commuting per day, holding other variables constant.

To compute the OCT associated with this change, we first calculate the average marginal effect (AME) in levels of commuting time as a change of one dollar in gasoline prices. Given the elasticity β, the AME in levels can be derived using the ratio of the sample mean values of C ($\overline{C}$) and $GasPrice$ ($\overline{GasPrice}$) as:

$$AME = \beta^* \left(\frac{\overline{C}}{\overline{GasPrice}}\right) = \left(\frac{\partial log(C)}{\partial log(GasPrice)}\right)^* \left(\frac{\overline{C}}{\overline{GasPrice}}\right) = 0.278^* \left(\frac{43.172}{2.920}\right) = 4.112 \quad (3)$$

From Table 1, we observe that $\overline{C}$ equals 43.172 min per day, and $\overline{GasPrice}$ equals \$2.92 per gallon. Thus, the AME in levels is the product of $\beta = 0.278$, and the ratio between 43.172 and 2.920, resulting in approximately 4.112 min per one dollar increase in gasoline prices. This suggests that a one dollar increase in gasoline prices relates to an average increase of 4.112 min in daily commuting, all else being equal.

Finally, to find the OCT, we take the inverse of this AME and convert from minutes to hours:

$$OCT = \frac{60}{AME} = \frac{60}{4.112} = 14.591 \quad (4)$$

This calculation indicates that the OCT is approximately \$14.6 per hour. This implies that an increase in gasoline prices by \$14.6 would correspondingly increase the commuting time by one hour.

To assess the economic implications of this figure, we compare it with the average wage rate of \$21.81 per hour (expressed in constant 2015 dollars) in our sample. The OCT thus represents approximately 67 % of the average wage rate, suggesting potential productivity losses due to the time spent commuting daily.

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