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The gasoline price and the commuting behavior: Towards sustainable modes of transport

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The gasoline price and the commuting behavior: Towards sustainable modes of transport

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Abstract

This paper analyzes how gasoline price is related to the time workers in the US spend commuting by private vehicle, public transport, walking, or cycling. Using data from the American Time Use Survey for the years 2003-2019, and collecting data on gasoline price by state and year, we find that higher gasoline prices are related to less commuting by private car, and more commuting by public transport, walking, and cycling, the latter being transportation alternatives that are more eco-friendly. A 1% increase in gas prices is associated with an increase of 0.325%, 0.568% and 0.129% in the commuting time by public and physical modes (walking and cycling), respectively. By contrast, a decrease of 0.638% is found in the proportion of commuting done by private car. Furthermore, the elasticity differs by urban characteristics, showing relatively larger values in urban areas for private and public modes. By analyzing the relationship between commuting time, and gasoline prices in the US, our results may serve to inform future policies aiming to develop a low-carbon transport system, especially in urban areas where workers may be more affected by gasoline prices (and thus taxation).

Keywords: Commuting time, gasoline price, commuting mode, urban areas, American Time Use Survey.

JEL Classification: R40, J1, J22, D1, Q4, R4.

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1. Introduction

Commuting is a daily activity for millions of workers during their working days and has attracted much research attention. Studies have shown that daily commuting is linked to health problems and lower levels of well-being (Kahneman et al., 2004; Kahneman and Krueger, 2006; Stutzer and Frey, 2008; Hansson et al., 2011; Roberts et al., 2011; Hilbrecht et al., 2014; Rissel et al., 2014; Morris, 2015; Künn-Nelen, 2016; Giménez-Nadal and Molina, 2019; Simón et al., 2020), lower worker productivity (Grinza and Rycx, 2020) and increased sickness absenteeism (van Ommeren and Gutierrez-i-Puigarnau, 2011; Goerke and Lorenz, 2017; Ma and Ye, 2019; Giménez-Nadal, Molina and Velilla, 2022). Furthermore, commuting has opportunity costs in terms of other activities that could be done while commuting (Christian, 2012; Hilbrecht et al., 2014; Newman et al., 2014; Mattisson et al., 2015; Denstadli et al., 2017; Morris and Zhou, 2018; Nie and Sousa-Poza, 2018; Voulgaris et al., 2019; Chatterjee et al., 2020).

Private car use has been identified as one of the greatest contributors to greenhouse gas (GHG) emissions. For instance, GHG emissions from transportation amount to a quarter or more of all anthropogenic emissions in many countries (Guillingham and Munk-Nielsen, 2019). And according to calculations by the Environmental Protection Agency (EPA, 2022), in 2021, 27.2% of all GHG emissions in the USA came from the transportation sector, mainly in form of CO2 emissions, making up the largest share of US GHG emissions since 2016 (Bleviss, 2021). Mobility is a central topic for GHG mitigation, reflected in the 2015 Paris Agreement (PA) that points to the need to achieve sustainable transport systems for all by 2030 as part of sustainable development goals.

Given that for many people the main reason for driving the car is to get to work (Prakash et al., 2020), it is important to identify what forces underlie the use of the car and of alternative, "greener" modes of commuting, as a way to ensure sustainable and inclusive development (UNFCCC, 2015, 2016; Wang and Liu, 2015). An analysis of mode choice in commuting may serve as the basis for policies aimed at encouraging modal shifts to the least carbon-intensive travel options (Pye and Daly, 2015); that is, public transit and active mobility – walking or cycling — that are considered to be "zero carbon" and environmentally friendly travel alternatives for personal travel (Chapman, 2007; Gössling and Choy, 2015).[1] Moreover, strategies that encourage commuting using physically demanding modes of transport have the potential to improve the health of commuters (Andersen et al., 2000; Shannon et al., 2006; Lindström, 2008; Shephard, 2008; Hamer and

[1] Even public transit fits the definition of active mobility because it involves physical activity (Shannon et al., 2006).

Chida, 2008; Frank et al., 2010; Buehler et al., 2011; Oja et al., 2011; Furie and Desai, 2012; Sahlqvist et al., 2012; Wanner et al., 2012; Dhondt et al., 2013).

Despite that how individuals commute to/from work is a personal choice and there are many factors influencing travel mode choice (Woodcock et al., 2009; Paez and Whalen, 2010; Popuri et al., 2011; Wener and Evans, 2011; Olsson et al., 2013; Daly et al., 2014), it is necessary that planners know the consumer responses to changes in energy prices. Prior research has examined consumer responses to changes in carbon taxes (Davis and Kilian, 2011; Li et al., 2014; Giménez-Nadal and Molina, 2019), although the evidence points toward consumers responding differently to changes in taxes and in prices (Ghalwash, 2007; Scott, 2012), with greater elasticities for gasoline taxes than for prices (Davis and Kilian, 2011; Li et al., 2014). Hence, quantifying the relationship between fuel prices and commuting behavior, and mode choice for commuting trips, is critical for public policies. If a rise in gasoline price could make commuters substitute driving for more physically demanding modes of transport that are zero carbon emitting modes (active transport), pricing policies may represent an active solution for reducing car use.

Within this framework, this paper examines how commuting, and modes of transport while commuting, are related to gasoline price in the United States. To that end, we use data from the American Time Use Survey (ATUS) for the years 2003 to 2019 and data on gasoline prices from the Energy Information Administration (EIA, 2022). We find no association between gasoline prices and total time spent commuting, but significant associations between gasoline prices and the proportion of commuting made by modes of transport, mostly driven by a substitution from car use to public transport, and physical modes such as walking and cycling. We find that higher gasoline prices are associated with greater shares of commuting by green modes and lower shares by private modes, and we explore whether the results differ according to the urban/rural context, finding a stronger association in urban areas.

The contribution of the paper is twofold. First, we contribute to the analysis of the effect of gasoline price on commuting, focusing on mode choice. To the best of our knowledge, our study is the first to evaluate the effects of gasoline price increases over the past decades among commuting modes, which may help planners to devise and implement policies aimed at decreasing more polluting transportation modes. Second, we find the greatest substitution from more polluting modes of transport to more eco-friendly alternatives, in urban areas. This result highlights the importance of prices in adopting energy-efficient technologies in urban areas, and posits gasoline prices as an important factor in reducing carbon emissions. Our results have important implications for the efficacy of pricing policies, such as fuel taxes or a carbon policy that pursues reductions in GHG emissions. In the current context of an energy crisis due to the war in Ukraine, our results support the idea that higher gasoline prices could generate an increase in alternative, greener transportation modes for commuting, reducing GHG emissions.

Section 2 of the paper presents the ATUS data, the sample, and the variables used in the analysis. Section 3 describes the econometric strategy, and Section 4 presents a discussion of the main results. Finally, Section 5 concludes.

2. Data and variables

We use data from the 2003-2019 American Time Use Survey (ATUS) to analyze the commuting behavior of workers in the US. The ATUS database, a joint project conducted continuously by the US Census Bureau and sponsored by the Bureau of Labor Statistics (BLS), is considered the official time use survey of the US and provides information of individual time use, where respondents are asked to fill out in their own words a diary summarizing episodes of the prior day (weekdays or weekend).[2] The ATUS asks one person per household over age 15 who has successfully completed the Current Population Survey (CPS) 2-5 months before, randomly chosen, to sequentially describe their activities during a 24-hour period (from 4:00 a.m. to 4:00 a.m. of the next day) about the day preceding the day of the interview (the "diary day").[3] For each episode, the ATUS collects the start and stop times, and thus we are able to add up the time spent participating in any given reference activity (e.g., paid work, leisure, childcare, market work, commuting, personal care, housework).[4]

[2] The ATUS is primarily conducted by telephone, but special provision is made to reach those whom it is imposible to reach by phone. Surveys are conducted in English and Spanish and have a conversational structure. We accessed the data using the American Time Use Survey Extract Builder (https://www.atusdata.org/atus/).

[3] Activities are coded according to a pre-existing scheme that includes over 17 major categories and 471 sub-categories at the most detailed level which provide highly precise information and in-depth look on how respondents spend their time. The major activity categories include: 'personal care', 'household activies', 'caring for and helping household members', 'caring for and helping non-household members', 'working and work-related activities', 'education', 'consumer purchases', 'profesional and personal care services', 'household services', 'government services and civic obligations', 'eating and drinking', 'socializing, relaxing and leisure', 'sports, exercise and recreation', 'religious and spiritual activies', 'volunteer activies', 'telephone calls', and 'travelling'. There are 83 sub-categories of travel purposes; the "travel related to working" sub-category (activity code 180501) is the focus of this paper.

[4] For a more detailed description of the survey, we refer the reader to Hamermesh et al. (2005) and Frazis and Stewart (2012).

The diaries are completed by respondents on selected days and include harmonized information about main activity, features such as the location of activity, the mode of transport, and whether the activity was performed in the company of another person. The advantage of self-reported diary data over other datasets, is that diary-based estimates of time use are more precise and reliable (Bianchi et al., 2000; Bonke, 2005; Aguiar and Hurst, 2007; Guryan et al., 2008; Kan, 2008; Giménez-Nadal and Sevilla, 2012; Harms, Berrigan and Gershuny, 2019).[5]

Given that commuting is done by workers, we restrict the sample to those who filled-in their diaries on working days, defined as days individuals spend at least 60 minutes on market work activities, excluding commuting (Giménez-Nadal, Molina and Velilla, 2018a, 2018b, 2020). Individuals with missing information on the variables used in our analysis are excluded and we drop those observations than can be considered outliers using the Blocked Adaptative Computationally Efficient Outliers Nominators (BACON) algorithm (Billor et al., 2000). The analysis is then performed at the individual level, and these restrictions give us a final sample of 60,911 workers, from the original 210,586 respondents of the pooled 2003-2019 ATUS data.

The dependent variables are the commuting time of workers in minutes per day, and the percentage of commuting time by the different modes of transport.[6] 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 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. In our analysis we calculate, and distinguish among, the proportion of commuting time that is done by private vehicle, public transit, walking, and cycling, defined as the time devoted to commuting using the reference mode of transport divided by the total time in commuting.

The main explanatory variable is the gasoline price. This information was collected from the EIA and is measured in gallons per million British Thermal Unit (BTU) by state (50 states plus District of Columbia) and year.

[5] One limitation of time use surveys is that commuting distance is not available. However, commuting time is usually the interest of transport and urban economics and commuting time and distance are highly correlated (Small and Song, 1992; Rietveld et al., 1999; Roberts et al., 2011; Dickerson et al., 2014).

[6] We define the commuting time variable as the sum of all episodes reported by each worker throughout the diary day.

In addition, we consider several socio-demographic and geographic characteristics of respondents from the ATUS that can be correlated with commuting time. We consider the gender of workers, defined as a dummy that takes value 1 for males, and 0 for females. Respondent's age is defined as a continuous variable measured in years and we include age and its square (divided by 100) to allow for any non-linear effects of age on commuting. The maximum level of formal education achieved by respondents is defined by three dummy variables, identifying individuals who have completed primary education, secondary education, or University education, respectively. Primary education is defined as not being a high school graduate, secondary education is defined as having a high school diploma, and University education is defined as having at least some college but no degree. We also create a dummy variable equal to 1 for those full-time workers (0 otherwise) and include the hourly earnings ($/hour).[7]

The marital status of respondents is defined as a dummy variable that takes value 1 for those who cohabit with a (married or unmarried) partner, and 0 otherwise, and we define a binary variable that takes value 1 where the respondent's partner is employed, 0 otherwise. The presence of children in the household is defined by three variables: a dummy variable that takes value 1 if respondent has a child between 0 and 5 years old, another dummy variable that takes 1 if the child is between 6 and 17 years old, and the total number of children under 18 in the household. Household income refers to the combined income of all family members during the last year and includes wages; net income from business, farm, or rent; pensions; dividends; interest; Social Security payments; and any other monetary income received by family members who are 15 years of age or older. We take into account the household total income coded with three income brackets ('Low income': <$25,000; 'Medium income': $25,000-$75,000; 'High income': >$75,000).[8]

Table 1 shows descriptive statistics for the variables of interest. On average, workers in the sample commute for 36 minutes. Among mode shares in commuting, the most frequent mode is private vehicle, and more than 94 per cent of the commuting time is done by car, truck, or motorcycle; 2.41% of the commuting time is spent on public transit, 2.93 % walking, and 0.41 per cent by bicycle. Males account for slightly more than half of the sample (53.4%) and workers report being aged about 40 years old; 10.4% of workers do not have a high school degree, 27.1% have achieved the high school diploma, and 62.4%

[7] Information on hourly earnings is given directly by most respondents in the ATUS, and for those who do not report hourly earnings we compute them as weekly earnings divided by the hours usually worked per week.

[8] In the ATUS, household income is measured as an ordinal variable using different income categories. We recode this variable in three income brackets.

have at least some college. Besides, 80.7% of workers are full-time employed and earn on average $20.55/hour. Regarding the household composition, 59.3% of the sample live with a partner, 44.4% have a working partner, and the average number of children under 18 in the worker's household is 0.807, while 17.8% and 25.7% of workers have children aged between 0 and 5, and between 6 and 17, respectively. Finally, 12.5% of households have an income of less than $25,000, 43.4% between $25,000-$75,000 and 38.7% more than $75,000.

The ATUS also contains information on the geographic location of the respondents. It could be that workers respond differently to shocks in gasoline price, depending on the location of residence. It is well-known that there are remarkable differences in infrastructure in these areas and, as a result, the price effects could differ. For instance, a gasoline price rise could be accompanied by a substitution of private vehicle to public transit in metropolitan areas, given the greater availability of these modes, whereas in a rural area the infrastructures are lower. At this point, it includes the metropolitan city status of the respondent and, from this variable, we create a dummy variable that takes value 1 if the worker is in a metropolitan (i.e., urban) area ('Metropolitan, central city', 'Metropolitan, balance of MSA', 'Metropolitan not identified'), and 0 otherwise (i.e., rural). Table 2 shows the average time devoted to commuting and the percentage of commuting done by modes of transport in urban and rural areas, along with p-values for the differences between metropolitan and rural areas. According to the 2003-2019 ATUS, there are large differences between urban and rural areas in relation to commuting. Among workers in metropolitan areas, the average commuting time is 37 minutes per day, whereas the percentage of commuting spent by private vehicle, public transport, walking, and cycling is 93.7, 2.78, 3.1, and 0.43%, respectively. For rural areas, the average commuting time is 30.67 minutes per day, and the percentage of commuting done by private vehicle, public modes, walking, and bicycle is 97.25, 0.43, 2.02, and 0.3 per cent.

Differences between urban and rural areas in terms of commuting and percentage of commuting by transportation modes, particularly by private vehicle, public transport, and walking, are statistically significant at standard levels (99% confidence level). Nevertheless, the differences between percentage of commuting by bicycle in urban and rural areas is only statistically significant at the 90% confidence level. Thus, there are differences, as could be expected, in the modes of commuting according to the geographic characteristics of the workers' area of residence, and workers living in urban areas have a greater probability of using more eco-friendly modes of transport.

3. Econometric strategy

We estimate Ordinary Least Squares (OLS) regressions on the time devoted to commuting. Although the dependent variables (commuting time/proportion of commuting by transport modes) may include zero values for some workers, where Tobit models (Tobin, 1958) could be preferred to account for censoring (some workers report no time in commuting or no time spent commuting by specific modes of transport), prior research when studying time allocation decisions has shown that results are similar using both OLS and Tobit models (Frazis and Stewart, 2012; Gershuny, 2012; Foster and Kaleskoski, 2013) Thus, we show OLS models for simplicity, despite that the results when estimating Tobit models are robust.

For a given individual "i", consider that C_{ijt} represents the daily minutes individual "i" living in state "j" in year "t" devotes to travel to/from work. We estimate the following linear equation to test the impact of gasoline price on commuting time:

$$\log(1 + C_{ijt}) = \alpha + \beta \log(GasPrice_{jt}) + \gamma X_{ijt} + \delta Year_{ij}^{l} + \varphi Day_{ij}^{n} + \varepsilon_{ijt} \quad (1)$$

where $GasPrice_{jt}$ is the gasoline price of state "j" in year "t", X_{ijt} denotes a vector of socio-demographic/control characteristics of individual "i" in state "j" and year "t" and ε_{ijt} is the error term that represents unmeasured variables and measurement errors. We transform the dependent variables and the gasoline price to their log form in order to interpret the estimated coefficients as elasticities.[9] We also include several vectors of variables to measure time ($Year_{ij}^{l}$, Day_{ij}^{n}). $Year_{ij}$ is a vector of year dummy variables (ref.: 2019, l=17), and Day_{ij}^{n} is a vector of day-of-week dummy variables (ref.: Sunday, n =7). These dummy variables take value 1 if the diary of individual "i" in state "j" refers to the n-th day and l-th year, and 0 otherwise. Thus, reference diaries refer to Sundays of 2019. We include these fixed effects in order to partially capture differences between days and years.

The vector X_{ijt} includes various characteristics of workers that may be correlated with commuting time. These variables are age (measured in years) and its square, maximum level of education achieved (ref.: primary education), the gender of the respondent (1 if male), whether the respondent is cohabiting (1 if yes), the number of children, the presence of children (aged 0-5 and 6-17) in the household, the household income (ref.: less than \$25,000), hourly wage, full-time status (1 if worker is a full time employee) and the

[9] We add a value equal to one in the commuting time, in order to impute an effective value equal to zero for those workers who report zero commuting and do not omit these respondents from the analysis (the log of zero is undefined). The +1 adjustment creates minimal distortion to the original commuting time variable.

employment status of the partner (1 if partner works). Estimates include robust standard errors to account for potential heteroscedasticity, and observations are weighted at the individual-level using demographic survey weights.[10]

We analyze the percentage of commuting done by private vehicle, public transit, walking and cycling. To that end, we estimate the following linear equation where the percentage of commuting done by transport mode is used as dependent variable:

$$\log(1 + p_{ijt}) = \alpha + \beta \log(GasPrice_{jt}) + \gamma X_{ijt} + \delta Year_{ij}^{l} + \varphi Day_{ij}^{n} + \varepsilon_{ijt} \quad (2)$$

Thus, we estimate OLS models considering five different dependent variables: the commuting time and the proportion of commuting time done by private vehicle, public transit, walking, and cycling. Despite that percentages are measured on a 0-1 scale, we sum the unity to the variable in order to have original dependent variables higher than 1.

To examine whether the relationship between gasoline price and commuting differs depending on the spatial character of the state where workers reside, we also estimate the following equations:

$$\log(1 + C_{ijt}) = \alpha + \beta_G \log(GasPrice_{jt}) + \beta_{METRO} METRO_{ij} + \beta_I \log(GasPrice_{jt}) * METRO_{ij} + \gamma X_{ijt} + \delta Year_{ij}^{l} + \varphi Day_{ij}^{n} + \varepsilon_{ijt} \quad (3)$$

$$\log(1 + p_{ijt}) = \alpha + \beta_G \log(GasPrice_{jt}) + \beta_{METRO} METRO_{ij} + \beta_I \log(GasPrice_{jt}) * METRO_{ij} + \gamma X_{ijt} + \delta Year_{ij}^{l} + \varphi Day_{ij}^{n} + \varepsilon_{ijt} \quad (4)$$

Where the variable $METRO_{ij}$ is a dummy variable that takes the value 1 if respondent lives in an urban area, and the interaction $\log(GasPrice_{jt}) * METRO_{ij}$ is included to test potential differences between the time devoted to commuting and gasoline price, according to the urban status of workers' residence, beyond the raw correlations between commuting time and gasoline price, on the one hand, and commuting time and urban characteristics, on the other hand.

4. Results

The results of estimating Equations (1) and (2) are shown in Table 3. We observe that gasoline price and commuting time are not correlated at standard significance levels, suggesting that commuting time does not depend on gasoline price. However, the proportion of commuting time spent by private car is negatively correlated with gasoline

[10] Variance inflation factors (VIFs) reveal no multicollinearity problems.

price, whereas the percentage of commuting by greener alternatives (i.e., public transit, walking, and cycling) is positively and significantly correlated with gasoline price. Specifically, a 1% increase in gasoline price is related to a greater proportion of time commuting by public transit, walking, and cycling, of 0.325%, 0.568%, and 0.129%, respectively. On the other hand, an increase of 1% in gasoline price is associated with a -0.638% proportion of commuting by car. Thus, higher gasoline price is negatively related to the proportion of driving by private vehicle, while they are positively related to the proportion of commuting by public transit, walking, and cycling, and the reduction in driving from higher gasoline price is fully compensated by more time commuting by public transit, walking, and cycling.

When we analyze the possible differential effects of gasoline price according to the location of workers – Table 2 shows that commuting time and the proportion of commuting by transport modes differ according to the urban status of the area of residence — Table 4 shows the results of estimating Equations (3) and (4). We first observe that there are no statistically significant differences between urban and rural areas in the commuting time and the proportion of commuting by modes of transport. But regarding the relationship between commuting and commuting mode, on the one hand, and gasoline price on the other, the interaction term between gasoline price and metropolitan residence displays statistically significant coefficients for the proportion of commuting by car and public transit. More specifically, an increase of 1% in gasoline price decreases the proportion of commuting by car by 0.462% in rural areas, whereas those workers who reside in urban areas decrease their proportion of commuting by car by 0.653% as a consequence of an increase of 1% in gasoline price. Those workers who reside in urban areas increase their share of commuting by public modes by 0.301% as a result of an increase by 1% in gasoline price, vs an increase of 0.251% in rural areas. Consequently, the relationship between gasoline price and the proportion of commuting by car and public transit, the two most frequent modes of travel to/from work in the US, is more intense, in absolute terms, in urban areas than in rural areas.

Regarding socio-demographic characteristics, males devote comparatively more time to commuting and a greater share of their commuting is done by bicycle. For age, we find a positive correlation with the time devoted to commuting and the proportion of commuting by private car and public transit, with an inverted U-shaped association. We find a negative relationship between University education and commuting time. Secondary education is negatively related to the proportion of commuting by public transit and walking, whereas those workers who have achieved secondary education devote a larger proportion to private vehicle. University education is negatively associated with the proportion of commuting time by public transit, and positively related to the percentage of commuting by bicycle.

The relationship found between full-time status of workers and total commuting time is positive and statistically significant at standard confidence levels, and full-time workers commute for more time than part-time employees. We observe a positive relationship between being a full-time employee and the proportion of commuting by private car, whereas full-time work is associated with a negative relationship to the percentage of commuting time spent walking. Hourly earnings are positively related to commuting time and the proportion of commuting by public transit and walking, whereas it is negatively associated with the proportion of commuting by private car. Thus, for those who earn more, there is a substitution from private car to public transit and walking.

Regarding household characteristics, household composition appears to be significantly correlated with commuting time and the proportion of commuting done by modes of transport. We observe that when workers live in couple they devote more time to commuting, even though their partner works. Those who live with a partner devote a larger proportion to commuting by private vehicle, and a lower proportion of their commuting is done by public transit and walking. Finally, the presence of children aged 0-5 or 6-17 is negatively associated with commuting time and the proportion of commuting done by green alternatives (public transit, walking, and cycling), while the presence of children aged less than 5 years in the household increase the share of commuting done by car.

5. Conclusions

This paper analyzes how gasoline price relate to commuters' travel time and mode choice, with a focus on differences between urban and rural areas. To that end, we use data from the American Time Use Survey for the period 2003-2019 and compute the total commuting time, and the percentages of commuting done by private vehicle, public transit, walking, and cycling. The results suggest that gasoline price is not correlated with the total commuting time, but that significant associations exist between these prices and the percentage of commuting done by car, public transit, walking, and cycling. More specifically, we find positive correlations between gasoline price and the proportion of commuting by public modes, and active/physically-demanding modes (walking and cycling), while this association displays a negative sign for private modes (car, truck, or motorcycle, both as driver or passenger). Furthermore, there are differences across urban areas, and when we account for these differences, we find stronger relationships between gasoline price and the percentage of commuting by private and public modes of transport across urban areas.

Our results suggest that higher gasoline price lead to lower levels of commuting by private vehicles, and greater levels of environmentally friendly transportation modes. Furthermore, considering pricing measures, such as a carbon tax that pursues the reduction of personal vehicle use, our results suggest that the instrument should be more effective in urban areas, in comparison to rural areas. These results must be considered by planners due to the importance of the transportation sector as the most prevalent GHG emissions transmitter (Bleviss, 2021; EPA, 2022).

Considering the ongoing energy crisis in the world due to the war in Ukraine, policy makers should take our findings seriously and the results of this work have significant implications for society, from the point of view of both environmental and tax policies. The results are important for the environment, as increases in gasoline price is associated with a higher proportion of transport by green modes (public transit, walking, cycling). Consequently, policy makers have an instrument via taxes to change the daily transport patterns of their citizens to greener transportation modes. However, these pricing policies would disproportionately affect a subset of workers, those outside urban areas, since their behavior is more rigid.

A very promising line of future research of the work presented here would be to extend the analysis to other travel, to test whether our results are generalizable. We demonstrate that gasoline price influence modes of commuting - private vehicle, public transit, walking and biking - but may also influence other trips that require driving, such as housework, leisure, childcare, or personal care travel. However, we should remember that such travel is not compulsory and represents a lower amount of our time.

The present analysis has certain caveats that merit mention. First, the nature of our data, a cross-section of individuals, limits our ability to infer causal relationships and we cannot account for endogeneity. Consequently, our results should be interpreted as conditional correlations. Despite the fact that the ATUS survey has been fielding annual time use diary data on a continuous basis since January 2003, the respondents interviewed are not the same every survey year and we cannot use panel data estimators. However, to our knowledge, time use surveys based on diaries are exclusively cross-sectional (i.e., respondents are observed only once). Second, we should note that the fit of the models is limited, and R-squared statistics range from 0.006 to 0.086, despite the addition of several control covariates. Nevertheless, we should remember that these limited predictive powers are the norm in commuting research (Giménez-Nadal and Molina, 2016, 2019; Giménez-Nadal et al., 2018, 2020).

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Table 1. Summary statistics

	Mean	Std. Dev.
Dependent variable:		
Commuting time	36.002	38.019
Percentage of commuting by private vehicle	94.253%	22.175
Percentage of commuting by public transport	2.410%	14.131
Percentage of commuting walking	2.929%	15.061
Percentage of commuting cycling	0.408%	6.247
Socio-demographics/controls:		
Being male	0.534	0.499
Age	39.809	13.923
Primary education	0.104	0.306
Secondary education	0.271	0.445
University education	0.624	0.484
Full time employee	0.807	0.394
Hourly earnings	20.554	15.123
Living in couple	0.593	0.491
Spouse work	0.444	0.497
Number of children <18	0.807	1.116
Children aged 0-5	0.178	0.382
Children aged 6-17	0.257	0.437
Low income (<$25,000)	0.125	0.330
Medium income ($25,000-$75,000)	0.434	0.496
High income (>$75,000)	0.387	0.487

Notes: Statistics are computed using sample weights included in the survey. Sample is restricted to workers who spend more than 60 minutes in market work activities excluding commuting.

Table 2. Summary statistics commuting time by metropolitan area

	Metropolitan		Rural		
	Mean/proportion	Std. Dev.	Mean/proportion	Std. Dev.	Difference
Commuting time	37.021	38.122	30.667	37.197	6.354***
Percentage of commuting by private vehicle	93.695%	23.173	97.251%	15.454	-3.556%***
Percentage of commuting by public transit	2.776%	15.122	0.432%	6.289	2.345%***
Percentage of commuting walking	3.098%	15.378	2.017%	13.131	1.081%***
Percentage of commuting cycling	0.431%	6.413	0.300%	5.410	0.131%*

Notes: Statistics computed using sample weights provided included in the survey. Sample is restricted to workers who spend more than 60 minutes in market work activities excluding commuting. Differences calculated as the mean (or proportion) values of commuting in urban areas minus the mean (or proportion) values in rural areas. *, **, and *** denote significance at the 90%, 95%, and 99% confidence level, respectively.

Table 3. Commuting time, proportion of commuting by mode of transport and gasoline price

Explanatory variables	(1) Commuting time	(2) % car	(3) % public	(4) % walking	(5) % cycling
Log of gasoline price	0.168	-0.638***	0.325***	0.568***	0.129***
	(0.128)	(0.158)	(0.051)	(0.076)	(0.032)
Being male	0.137***	-0.012	-0.003	0.017*	0.013***
	(0.016)	(0.021)	(0.008)	(0.009)	(0.004)
Age	0.039***	0.033***	0.006***	0.003	0.000
	(0.004)	(0.005)	(0.002)	(0.002)	(0.001)
Age^2	-0.044***	-0.034***	-0.007***	-0.005*	-0.001
	(0.004)	(0.005)	(0.002)	(0.002)	(0.001)
Secondary education	0.054*	0.259***	-0.067***	-0.040**	0.003
	(0.030)	(0.039)	(0.016)	(0.018)	(0.004)
University education	-0.075**	0.021	-0.038**	0.003	0.014***
	(0.030)	(0.038)	(0.016)	(0.017)	(0.005)
Full time employee	0.517***	0.616***	-0.006	-0.035**	0.005
	(0.025)	(0.033)	(0.012)	(0.015)	(0.006)
Log of hourly earnings	0.050***	-0.153***	0.044***	0.034***	-0.004
	(0.017)	(0.022)	(0.010)	(0.010)	(0.004)
Living in couple	0.166***	0.194***	-0.052***	-0.065***	-0.004
	(0.024)	(0.030)	(0.013)	(0.014)	(0.004)
Spouse work	-0.070***	0.022	-0.017	0.007	0.001
	(0.023)	(0.027)	(0.011)	(0.012)	(0.004)
Number of children <18	-0.011	-0.015	0.006	0.009	-0.000
	(0.012)	(0.015)	(0.008)	(0.007)	(0.001)
Children aged 0-5	-0.067**	0.082**	-0.030	-0.080***	-0.033***
	(0.032)	(0.040)	(0.019)	(0.019)	(0.005)
Children aged 6-17	-0.099***	0.002	-0.050***	-0.065***	-0.027***
	(0.028)	(0.035)	(0.016)	(0.015)	(0.003)
Medium income ($25,000-$75,000)	-0.004	0.125***	-0.042***	-0.084***	-0.016**
	(0.021)	(0.028)	(0.012)	(0.014)	(0.007)
High income (>$75,000)	-0.083***	-0.020	-0.041***	-0.090***	-0.019***
	(0.026)	(0.034)	(0.013)	(0.016)	(0.007)
Constant	0.505	3.984***	-0.965***	-1.559***	-0.361***
	(0.397)	(0.491)	(0.160)	(0.233)	(0.092)
Observations	60,911	60,911	60,911	60,911	60,911
R-squared	0.083	0.069	0.008	0.010	0.006

Notes: The ATUS (2003-2019) has been restricted to employees on their working days. Estimates are weighted using demographic survey weights. Robust standard errors reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

Table 4. Commuting time, proportion of commuting by mode of transport, gasoline price and interaction effect

Explanatory variables	(1) Commuting time	(2) % car	(3) % public	(4) % walking	(5) % cycling
Log of gasoline price	0.154	-0.462***	0.251***	0.546***	0.117***
	(0.143)	(0.177)	(0.052)	(0.084)	(0.031)
Urban area	0.438*	0.522*	-0.061	0.048	-0.036
	(0.227)	(0.279)	(0.069)	(0.112)	(0.036)
Log of gasoline price * Urban	-0.072	-0.191**	0.050**	0.004	0.013
	(0.075)	(0.092)	(0.022)	(0.037)	(0.012)
Being male	0.141***	-0.008	-0.002	0.017*	0.013***
	(0.016)	(0.021)	(0.008)	(0.009)	(0.004)
Age	0.039***	0.034***	0.006***	0.002	0.000
	(0.004)	(0.005)	(0.002)	(0.002)	(0.001)
Age^2	-0.044***	-0.035***	-0.007***	-0.004*	-0.001
	(0.004)	(0.005)	(0.002)	(0.002)	(0.001)
Secondary education	0.066**	0.261***	-0.064***	-0.037**	0.003
	(0.030)	(0.039)	(0.016)	(0.018)	(0.004)
University education	-0.077***	0.024	-0.040**	0.003	0.015***
	(0.030)	(0.038)	(0.016)	(0.017)	(0.005)
Full-time employee	0.518***	0.613***	-0.003	-0.035**	0.005
	(0.025)	(0.033)	(0.012)	(0.015)	(0.006)
Log of hourly earnings	0.036**	-0.149***	0.038***	0.030***	-0.004
	(0.017)	(0.022)	(0.010)	(0.010)	(0.004)
Living in couple	0.175***	0.192***	-0.048***	-0.063***	-0.004
	(0.024)	(0.030)	(0.013)	(0.014)	(0.004)
Spouse working	-0.066***	0.020	-0.016	0.009	0.001
	(0.023)	(0.027)	(0.011)	(0.012)	(0.004)
Number of children<18	-0.011	-0.015	0.006	0.007	-0.000
	(0.012)	(0.016)	(0.008)	(0.007)	(0.001)
Children aged 0-5	-0.069**	0.080**	-0.030	-0.079***	-0.033***
	(0.032)	(0.041)	(0.019)	(0.019)	(0.005)
Children aged 6-17	-0.100***	-0.003	-0.049***	-0.064***	-0.027***
	(0.028)	(0.035)	(0.016)	(0.015)	(0.003)
Medium income ($25,000-$75,000)	-0.004	0.125***	-0.043***	-0.083***	-0.016**
	(0.021)	(0.028)	(0.012)	(0.014)	(0.007)
High income (>$75,000)	-0.097***	-0.017	-0.046***	-0.094***	-0.020***
	(0.026)	(0.034)	(0.013)	(0.016)	(0.007)
Constant	0.389	3.472***	-0.805***	-1.532***	-0.328***
	(0.442)	(0.547)	(0.162)	(0.255)	(0.089)
Observations	60,479	60,479	60,479	60,479	60,479
R-squared	0.086	0.069	0.010	0.011	0.007

Notes: The ATUS (2003-2019) has been restricted to employees in their working days. Estimates are weighted using demographic survey weights. Robust standard errors reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.