Green commuting and gasoline taxes in the United States*

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Abstract:

This paper analyzes how gasoline tax rates are related to the time workers in the United States spend commuting by private car, public transport, or with other physical modes of transport. Our identification strategy relies on both inter-state differences and time variations in gasoline taxes. Using the American Time Use Surveys for the years 2003 to 2015, we find that higher gasoline tax rates are related to less time spent in commuting. Furthermore, higher gasoline taxes are related to less commuting by private car, and more commuting by public transport and/or a physical mode of transport (walking or cycling). Our results highlight the importance of gasoline taxes in the consumption of energy for personal transport, as higher gasoline taxes are related to a greater use of

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"green" modes of transport, showing that fuel taxes are important for good environmental management.

Keywords: commuting time, public transport, walking/cycling, gasoline taxes.

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1. Introduction

In this paper, we analyse the relationship between the commuting behaviour of workers in the United States and gasoline taxes, with a focus on driving and "green" modes of personal transport (i.e., public transport and walking/cycling). The United States is among the countries with the highest consumption of gasoline in the world (over 130 billion gallons of gasoline annually, Gilligham et al., 2015), generating around one-third of the US greenhouse gas (GHG) emissions of the country (EPA, 2014). In order to implement efficient policies aimed at decreasing the consumption of energy, GHG emissions, and improving management of the environment, policymakers need to know the effects of different policy measures, such as increasing fuel taxes, or the Zero Emissions Vehicle (ZEV) mandate, both of which critically depend on the behavior of consumers. Thus, it is important to analyse the consumer response to changes in fuel taxes in their private transport decisions, and we here focus on the relationship between commuting time and gasoline taxes.

Despite that consumers may respond differently to changes in taxes than to changes in prices (Li et al., 2014), it is expected that consumers will respond similarly to each of those factors. Prior research has found negative price elasticities for the consumption of gasoline, based on driving behavior (Dahl and Sterner, 1991; Greening et al, 2000; Small and Van Dender, 2007; Hughes et al., 2008; Burke and Nishitateno, 2013; Gillighan, 2014; Hymel and Small, 2015; Chen et al., 2017), and similar evidence has been found for the relationship between gasoline taxes and the consumption of gasoline (Dahl, 1979; Goel, 1994; Bento et al., 2005; Li et al., 2014, Liu, 2015). But the research to date has focused on the effect of gasoline taxes/prices on driving, leaving aside other modes of transport. Such analysis is relevant, as it has implications for GHG emissions. For instance, the use of public transport may be beneficial for the environment in comparison to private vehicles, as it helps to reduce GHG emissions (Stanley and Watkiss, 2003; Chapman, 2007; Gôssling and Choy, 2015; Holian and Kahn, 2015). Also, the use of physical modes of transport contribute more to the reduction of GHG emissions as they are, ultimately, 'zero carbon' and an environmentally friendly solution for personal transport (Chapman, 2007). Thus, in order to have a complete view of the effect of tax instruments, we need to ask whether the reduction in driving due to an increase in fuel taxes devolves to a greater use of public transport, if it results in more walking/cycling, or both.

Within this framework, we analyze how the time workers spend driving to/from work (commuting), and using "green" modes of transport, such as public transport and walking/cycling, are affected by gasoline tax rates.To that end, we use the 2003-2015 American Time Use Survey (ATUS) to measure the commuting time of workers in the US. Millions of workers in the US commute every working day (on average 45 minutes per day, according to Gimenez-Nadal and Molina, 2016, and Gimenez-Nadal, Molina and Velilla, 2018a, 2018b). This activity, obviously, contributes to the overall consumption of energy. Gasoline tax rates differ by State, and may also change over time at the State level, which allows us to analyze how these differences over time and across States are related to consumer behavior. We analyze the relationship between the time devoted to commuting during a working day, and gasoline taxes. We also analyze the relationship between gasoline taxes and the proportion of daily commuting of three different modes of transport: private, public, and physical. Thus, we can determine whether reductions in the driving time of workers due to higher gasoline taxes are related to more time in commuting by public transport or physical modes of transport, or both.

Higher gasoline taxes are related to less time spent in commuting. To the extent that most of the commuting in the US is done by car, our results can be interpreted as a negative relationship between private car use and gasoline taxes, which is consistent with prior evidence on the intensive margin of driving. We also observe that higher gasoline taxes are related to a lower proportion of commuting time by private car, and to a higher proportion of commuting time by both public transport and physical modes of transport. In other words, higher gasoline tax rates are related to a substitution from driving to alternative “green” modes of transport.

Our contribution to the literature is twofold. First, we contribute to the analysis of the effect of gasoline taxes on driving for commuting to/from work, complementing prior analyses. To the best of our knowledge, time-use data has not previously been used in this context, and our results point to a negative effect of gasoline taxes on driving (negative price elasticity). Second, we add a new perspective to the analysis of fuel taxes and energy consumption, by including in the analysis “green” modes of personal transport that may substitute for driving. Our results shed light on the importance of these modes of transport in policy analysis, adding to the assessment of policies and gaining a more complete view of the effects of gasoline taxes on energy consumption and environmental management. Our results open a very promising line of research.

The rest of the paper is organized as follows. Section 2 describes the data and the variables of interest. Section 3 describes the empirical strategy, and Section 4 presents the main results. Finally, Section 5 sets out our main conclusions.

2. Data

We use the 2003-2015 American Time Use Survey (ATUS) to measure the commuting time of workers in the US. Respondents are asked to fill out a diary summarizing episodes of the preceding day, and thus the ATUS provides us with information on individual time use, based on diary questionnaires, in which individuals report their activities throughout the 24 hours of the day. The ATUS includes a set of activities, defined as the activity individuals were engaged in throughout the day, and we are able to add up the time devoted to any given reference activity (e.g., paid work, leisure, TV watching). The ATUS is administered by the US Bureau of Labor Statistics, and is considered the official time use survey of the country. (More information can be found at http://www.bls.gov/tus/.)

Several advantages of time use surveys are relevant to our purpose. First, they allow for an accurate measure of commuting time, in comparison with other datasets. We can distinguish between pure commuting episodes and other episodes that are ancillary activities, such as picking up children from school. Time use surveys provide information on duration, departure and arrival times, location, and mode of transport, and while they are inferior in comparison to other datasets, such as National Travel Surveys, they are complementary (Kitamura and Fuji, 1997). The use of time-use surveys in transportation research has become common (Gimenez-Nadal and Molina, 2014; 2016; Jara-Díaz and Rosales-Salas, 2015; Gimenez-Nadal, Molina and Velilla, 2018a, 2018b). One limitation of such surveys is that commuting distance is not available, so issues related to distance cannot be analyzed and commuting distance cannot be used to explain commuting time.

We restrict our sample to workers on their working days, defined as days individuals spend 60 minutes or more working (excluding commuting) and where commuting time is the time devoted to the activity "commuting to/from work", coded as "180501" in the ATUS codebook. We restrict the analysis to working days to avoid computing zero minutes of commuting for any worker who filled out the time use diary on a non-working day. The final sample consists of 115,923 workers who devote an average of 43.12 minutes per working day to commuting, with a standard deviation of 39.91 (see Table 1).

The ATUS also allows us to compute the percentage of total commuting time that is done using different modes of transport. The modes of transport are the following: Car, truck or motorcycle (driver); Car, truck or motorcycle (passenger); Walking; Bus; Subway, train; Bicycle; Boat, ferry; Taxi, limousine service; Airplane; and Other mode of transportation. From this classification, we consider three primary modes of transport: by private transport (Car, truck, or motorcycle as driver, or car, truck, or motorcycle as passenger), by public transport (bus, subway, train, boat, ferry, taxi, limousine service, or airplane) and by physical mode of transport (walking or bycicle). In our sample, the average proportions of commuting by private car, public transport, and physical mode are 91.61%, 2.70%, and 3.21%, respectively.

In the US, a federal tax rate of 18.4 cents/gallon is applied to gasoline (since 1993) in all States, and each State has the freedom to establish its own (additional) tax rate on gasoline. Thus, there exist inter-State differences in gasoline tax rates, and we examine these differences in our analysis. Data on gasoline tax rates for each state and year are obtained from the the Highway Statistics Series published by the Federal Highway Administration, US Department of Transportation. It can be seen that there are inter-State and over-time variations in gasoline tax rates (Table A1 shows state gasoline tax rates in the period 2003-2015). For instance, in 2003, the highest tax rates are in Connecticut and Rhode Island, while the lowest tax rates are in Alaska, New Jersey, and Wyoming. Furthermore, while in some States, tax rates have decreased, as in Oregon, Pennsylvania, and Idaho, in other States tax rates have been constant (e.g., Arizona, Michigan, and Oklahoma) or have increased (e.g., Maine, Nebraska, and Georgia) during the period under study. These variations allow us to relate changes in gasoline tax rates to changes in the commuting behavior of individuals.

When we consider the correlation between the time devoted to commuting and gasoline tax rates, we find a negative coefficient of -0.02. Considering the percentage of commuting by each mode of transport, we find a negative correlation coefficient of -0.03 between gasoline tax rates and the percentage of commuting by car, and positive correlations of 0.02 between gasoline tax rates and the percentage of transport by public transport and by physical modes of transport. These correlation coefficients are statistically significant at the 95 percent confidence level. In sum, we find that higher gasoline tax rates are associated with less time spent in commuting, and with a lower proportion of commuting time by private transport and a higher proportion of commuting by public transport or physical mode of transport. The evidence suggests that gasoline taxes could be used as a policy instrument to reduce GHG emissions, given the reduction in commuting time of workers and the shift towards green commuting modes that include public transport and physical modes of transport. However, this analysis does not take into account differences in worker characteristics, nor variations within States regarding traffic density and highway development. In the following Sections, we develop a more in-depth analysis.

3. Empirical strategy and variables

We estimate OLS regression on the time devoted to commuting, a model that has often been applied in prior research using time use data on commuting (Gimenez-Nadal and Molina, 2014; 2016: Gimenez-Nadal, Molina and Velilla, 2018a,2018b).[1] The statistical model is as follows: for a given individual "i", let C_{ijk} represent the (log) daily hours

[1] Given that the ATUS represents a cross-section of individuals, we cannot apply panel data estimators, which includes the Randon Effects (RE) and Fixed Effects (FE) estimators.

individual "i" living in State "j" (j=1,2…51) in year "t" (t=2003, 2004…2015) devotes to commuting, let $TaxRate_{jt}$ be the (log) gasoline tax rate in State "j" in year "t", let X_i be a vector of socio-demographic characteristics of individual "i" in State "j" and year "t", and let ε_{ijt} be random variables that represent unmeasured factors. We estimate the following equation:

$$\log(C_{ijt}) = \alpha + \beta \log(TaxRate_{jt}) + \gamma X_{ijt} + \partial TPI_j + \vartheta Year_{ij} + \vartheta State_{it} + \varepsilon_{ijt} \quad (1)$$

where C_{ijt} represents the time devoted to commuting. We transform both the dependent variable and gasoline tax rates to their log form so that the coefficient β from this regression can be interpreted in terms of elasticity, i.e. the percentage change in commuting time when gasoline tax rates increase by one percent.[2] We also include variables to measure time ($Year_{ij}$) and State ($State_{it}$) fixed effects, as the commuting behavior of individuals may differ, depending on factors such as weather conditions (Connolly, 2008) or economic conditions (Burda and Hamermesh, 2010; Aguiar, Hurst and Karabarbounis, 2013).

The vector X_{ijt} includes various characteristics of workers that may have a direct relationship to the time devoted to commuting. Given prior research showing that men and women have different commutes (Gimenez-Nadal and Molina, 2016), we take into account the gender of the worker. Other variables that may affect the time devoted to commuting are age of respondents, wages, education, whether the respondent lives in couple, labour status of spouse/partner, the number of children in the household, and the

[2] We transform commuting time, adding unity in order to avoid missing values that would correspond to zero commuting. Figure A1 in the Appendix shows the distribution of the log-transformed variable of commuting time, using kernel-density distributions. We observe that the transformed variable concentrates its values around 3.5, and the two tails resemble the shape of a normal distribution (added to the figure).

age of the youngest child in the household (see Gimenez-Nadal and Molina, 2016, Gimenez-Nadal, Molina and Velilla, 2018b, for a review of the expected relationships between socio-demographic characteristics and commuting time).

The variable for gender is a dummy variable that takes value "1" if respondent "i" is male, and value "0" otherwise. The variable measuring education in the ATUS includes 16 educational categories, and we define a zero/one binary variable for each educational category.[3] For those living in couple, we also control for whether the respondent's partner is working (1) or not (0), and computing value "0" for those who do not live in couple. We also control for the number of children under 18 years old in the household and for the age of the youngest child.

The ATUS includes information on labor earnings, which allows us to compute the hourly wage of workers. We have defined the hourly earning (wage rate) directly as earnings per hour, if this data is available from ATUS; in other cases, we have defined it as earnings per week divided by the usual weekly working hours. Given prior evidence showing a positive relationship between commuting and wages (Leigh, 1986; Zax, 1991,

[3] The ATUS includes the following categories: "Less than 1st grade", "1st, 2nd, 3rd, or 4th grade", "5th or 6th grade", "7th or 8th grade", "9th grade", "10th grade", "11th grade", "12th grade - no diploma," High school graduate - diploma or equivalent (GED)", "Some college but no degree," "Associate degree - occupational/vocational", "Associate degree - academic program", "Bachelor's degree (BA, AB, BS, etc.)", "Master's degree (MA, MS, MEng, MEd, MSW, etc.)", "Professional school degree (MD, DDS, DVM, etc.)", and "Doctoral degree (PhD, EdD, etc.)". An alternative to the use of educational dummies is the use of a continuous variable measuring years of education. However, the use of this latter variable would imply we were assuming a linear relationship between education and commuting time. To avoid this assumption, we use dummy variables for the education of individuals, although the use of a continuous variable for education does not change our main results. Results are available upon request.

White, 1999, Ross and Zenou, 2008, Fu and Ross, 2013, Mulalic, van Ommeren, and Pilegaard, 2014; Gimenez-Nadal, Molina and Velilla, 2018a), we need to control for the labor income of workers to net out the effect of tax rates on commuting from other effects (Shapiro and Stigliz, 1984).[4] We transform the hourly wage rate to its log form, in order to allow for a non-linear (diminishing) effect. We also include age transformed to its log form.[5]

We include the Transportation Performance Index (TPI), developed by the US Chamber of Commerce, which is part of the Infrastructure Performance Index series, a groundbreaking endeavor of the Chamber's 'Let's Rebuild America' (LRA) initiative. For each State, a value is assigned on this index, to measure the performance of transportation infrastructures. The index is based on a well-defined methodology, uses existing publicly-available data, and incorporates the major infrastructure sectors. The TPI is composed of 25 measures (e.g., route-miles per 10,000 population, fatalities per 100 million Vehicle Miles Traveled, Runway incursions per million operations), which are classified in three main categories: Supply, Quality of Service, and Utilization. Thus,

[4] Table 1 shows averages and standard deviations for our sample of workers. 55% are male, with an average age of 38.66; 28,7% of workers have a high school degree, 17.7% have some college although no degree, 20.1% hold a Bachelor's degree, and 6.7% have a doctoral degree. Furthermore, 67% of the sample live in couple and 49% have a working partner, the average number of children per household is 1.23, and the average age of the youngest child is 4.32 years. Finally, the average wage rate of workers in the sample is $19.51/hour.

[5] We also estimate all the regressions using a quadratic specification for age and hourly wages. The use of the log specification is preferable, given that the use of the quadratic specification may raise concerns associated with Environmental Kuznets curves (Grossman and Krueger, 1994). Results are robust to the use of the quadratic specifications, and are available upon request.

the TPI synthetizes performance of infrastructures in these three dimensions, which have been identified as important in shaping the transport behavior of individuals. The different measures are combined to give a single value, with higher values of the TPI indicating better performance of infrastructures. More information on the TPI can be found at https://www.uschamber.com/issue-brief/transportation-performance-index. The most recent TPI available at the State level is from the year 2010, which we use for our analysis. The highest values of the TPI correspond to North and South Dakota, and Nebraska, and the lowest values correspond to the District fo Columbia, New Jersey, and Hawaii (Table A2 in the Appendix shows the values assigned to the TPI for each State). When we compute the correlation between time spent commuting and the TPI, the correlation coefficient is -0.10 and statistically significant at the 99% level, indicating that workers devote less time to commuting, ceteris paribus, in States where the TPI is higher (i.e., better performance); that is, in States with higher performance in their infrastructure, workers need less time to get to their work places.

For the percentage of time commuting in each mode of transport, we also estimate OLS models, given the continuous nature of the dependent variables. Given that we compute the time workers spend during the daily commute using private, public, and physical modes of transport, any of the three variables can, in principle, take values from zero to one. The statistical model is as follows: for a given individual "i", let P_{ijk} represent the (log) percentage of time individual "i" living in State "j" (j=1,2…51) in year "t" (t=2003, 2004…215) spends commuting, by the reference mode of transport, let $TaxRate_{jk}$ be the (log) gasoline tax rate in State "j" at year "t", let X_i be a vector of socio-demographic characteristics of individual "i" in State "j" and year "t", and let ε_{ijt} be random variables that represent unmeasured factors. We estimate the following equation:

$$\log(P_{ijt}) = \alpha + \beta \log(Tax\_Rate_{jt}) + \gamma X_{ijt} + \partial TPI_j + \vartheta Year_{ij} + \vartheta State_{it} + \varepsilon_{ijt} \quad (2)$$

where $\log(P_{ijt})$ represents the (log+1)percentage of time in commuting spent in the reference mode of transport. The explanatory variables included in Equation (1) are also included in this analysis, and results can be interpreted in terms of elasticity.

4. Results

Column (1) of Table 2 shows the results of estimating Equation (1) of the (log) time devoted to daily commuting on gasoline tax rates. We observe a negative relationship between commuting time and gasoline tax rates, showing that a 1% increase in the gasoline tax rate is related to a 0.07% decrease in average daily commuting time (see Column 3). This result is consistent with the existing literature showing negative gasoline price elasticities, for driving, of around 0.10%. Columns (2), (3) and (4) of Table 2 show the results of estimating Equation (2) on the proportion of commuting by private transport, public transport, and physical modes of transport, on gasoline tax rates. We find that higher gasoline taxes are related to a decrease in the proportion of commuting by car, while being related to increases in the proportion of commuting by public transport or physical modes of transport. A one-percent increase in the gasoline tax rate is related to a 0.35% decrease in the proportion of daily driving commuting time, and with increases of 0.16% and 0.26% in the proportion of daily commuting time using public transport or a physical mode of transport, respectively.

In sum, we find a negative price elasticity of commuting time on gasoline tax rates, as higher taxes are related to less commuting time. Furthermore, higher gasoline taxes are negatively related to the amount of driving, while they are positively related to the proportion of commuting by public transport or physical modes. Thus, our results shed light on the effects of public policies, based on fuel taxes, on the driving behavior of workers. We note that the reduction in driving following from higher gasoline taxes is in part compensated for by more time walking or cycling, but also by a greater use of public transport. If the reduction in driving were fully compensated for by more time walking or cycling, public policies focusing on fuel taxes would certainly have more impact on energy consumption and GHG emissions than when public transport is also used. In order to design public policies aimed at decreasing energy consumption and GHG emissions, the extent to which driving is substituted for by public transport or physical modes must be fully considered.

Among the possible mechanisms explaining the negative relationship between gasoline taxes and commuting time, we find the reduction of traffic as a possible explanation. Less traffic is likely to reduce travel time to work (Parent and LeSage, 2010), especially for those who use their cars. We have observed that higher tax rates are related to a substitution from commuting by car, to commuting by public and physical modes of transport. So when gasoline taxes are relatively higher, those who still use their car for their commuting trips will find lighter traffic, which could explain the reduction of commuting time.[6] We must acknowledge here that a substitution from car use to public and physical modes of transport is likely to increase the time devoted to commuting, but most commuting in the US is done by private car – more than 90% of the commuting – so it is likely that the reduction in commuting time due to less time driving is greater than the increase in commuting time due to the substitution from car to public and physical modes of transport.

[6] We rely on the assumption that commuting distance does not change. Given that we do not have information on commuting distance, we cannot test whether less commuting time is also associated with less commuting distance.

One issue that must be considered in the analysis of gasoline taxes is the ability of individual States to pass on gasoline tax rates to consumers. The usual assumption, which is also used in the current framework, is that gasoline taxes are passed to consumers on a one-for-one basis. But recently, Kaufmann (2019) has shown that the rate at which taxes are passed to consumers varies among States, and that ignoring such differences may mask heterogenous effects. Taxes are passed to wholesale prices on a one-for-one basis in Florida and Massachusetts, are passed to retail prices with a "mark-up" in Florida, Massachusetts, New York, and Ohio, and are not fully passed through in Washington. In that case, and despite that our regressions control for the State of residence, we cannot control for these cross-state heterogeneous effects, and our results may be biased. In the current context, the effect of taxes on the commuting behavior of workers may be greater in States where prices increase by more than the tax, and smaller in States where prices increase by less than the tax.

Other results

Regarding the time devoted to commuting, we observe that male workers devote more time to commuting than do female workers, consistent with prior research showing gender differences in commuting behavior (Gimenez-Nadal and Molina, 2016). For both age and education, we find a positive correlation with the time devoted to commuting, given that the coefficients are positive and statistically significant at the 99 percent level. Since both age and hourly wage are in their log form, we can interpret these coefficients in terms of elasticity: a one percent increase in age and education is related to an increase of 10% and 16% of commuting time, respectively. Furthermore, the positive relationship between commuting and wages is consistent with the existing literature showing an increase in wages after an increase in commuting (Marimom and Zilibotti, 1999 ;

Manning, 2003, Van Ommeren and Rietveld, 2005; Ross and Zenou, 2008; Mulalic, Van Ommeren and Pilegaard, 2014). In the case of education, we do not find robust evidence of either a positive or negative relationship between education and commuting time. The coefficient for the category “12th grade-no diploma” is -0.228, while for “High school graduate – diploma or equivalent” it is -0.164, for “Doctoral degree (PhD, EdD, etc…)” it is -0.227, and it is not statistically significant for “Bachelor’s Degree (BA, AB, BS, etc)”.

Regarding household characteristics, we observe that, when workers live in couple they devote more time to commuting, but only if the partner does not work. If the partner works, the amount of commuting time is reduced. The presence of children under age 18 in the household presents a negative relationship to commuting time, especially when the children are young, consistent with the Household Responsibilities Hypothesis (i.e., parents, especially mothers, accept jobs closer to home in order to increase their availability for childcare responsibilities (Gimenez-Nadal and Molina, 2016).

Focusing on the proportion of commuting by the various modes of transport, we can determine a profile of those individuals who are more likely to use alternative modes of transport, such as public or physical. We observe that males have, in comparison to women, a lower probability of using public transport, as the relationship between the gender dummy (male) and the proportion of commuting by public transport is negative. Gimenez-Nadal and Molina (2016) show that this may be due to the Household Responsibilties Hypothesis, as responsibilities for childcare make women more dependent on public transport. Regarding education, we find that the educational categories "11th grade", "12th grade - no diploma", "High school graduate - diploma or equiv", "Some college but no degree", "Associate degree - occupational/vocatio", "Associate degree - academic program", "Bachelor's degree (BA, AB, BS, etc.)" are all related to a higher proportion of commuting by car, and to a lower proportion of commuting by public transport and physical modes of transport, in comparison with other educational categories.

Age is positively related to the proportion of commuting by public transport, and negatively related to the proportion of commuting by physical mode. Thus, for those who choose alternative modes of transport, there is a substitution from physical modes to public transport as individuals get older. Furthermore, we observe a positive relationship between hourly wages, on the one hand, and the proportion of commuting done by private and public transport, on the other. Hourly wages are negatively related to the proportion of commuting by physical modes of transport. Thus, income plays a role in the selection of the mode of transport, as those with higher incomes tend to choose modes of transport that are more expensive than physical modes of transport.

Those living in couple use private transport in a higher proportion, along with a lower proportion of use of both public and physical modes of transport, while those who have a working spouse have a lower probability of using physical modes of transport. The presence of children in the household is related to a greater use of public transport, although the younger the child, the greater the use of private transport in detriment to the use of public and physical modes of transport. Thus, it appears that childcare responsibilities condition the choice of mode of transport, and the presence of young children makes working parents rely more on private modes of transport. A higher value of the TPI is related to a greater use of private transport, and a lesser use of public and physical modes of transport. When the quality of infrastructure is better, workers will probably drive more often, which increases driving to/from work.

5. Conclusion and Policy Implications

The consumer response to changing gasoline prices has long interested economists and policymakers, as it has important implications for the effects of gasoline taxation and vehicle energy-efficiency policy. In this paper, we analyse the relationship between the commuting behaviour of workers in the United States and gasoline tax rates, introducing the analysis of “green” modes of transport as an important focus of research. Prior research has focused on the effect of gasoline taxes/prices on driving, leaving aside other modes of transport, and if a complete view of the effect of tax instruments is needed, the analysis of whether a reduction in driving is due to an increase in fuel taxes is essential.

We use the 2003-2015 American Time Use Survey (ATUS), and the inter-State and over-time variations in gasoline taxes, to identify the relationships in the time devoted to commuting. We find that higher gasoline taxes are related to less time spent in commuting, that higher gasoline taxes are related to a lower proportion of commuting by private car, and to a higher proportion of commuting by both public transport and physical modes of transport. Thus, higher gasoline taxes may lead to a substitution from driving to alternative “green” modes of transport.

Our results may be of interest for policymakers in the design of efficient policies aimed at decreasing energy consumption and GHG emissions. Increasing gasoline taxes is politically challenging, although the results show that increasing gasoline tax rates would result in substantial energy efficiency improvements, as other modes of transport come into play as substitutes for driving. Despite prior studies finding that gasoline consumption is quite inelastic to changes in prices (Liu, 2015; Gillingham et al., 2015), the results shown in this paper may help to design more efficient policies.

One important issue that emerges in the current analysis is that we cannot identify the relationship between commuting and gasoline tax rates net of individual heterogeneity in preferences. Given that the ATUS is a cross-section of individuals, we cannot apply panel data estimators. Thus, our results are based on the assumption that the coefficients associated with taxes are the same across individuals, although ignoring heterogeneous effects can lead to biased outcomes (Hsiao, 1986). For this reason, we cannot claim any causal link between tax rates and commuting time.

One limitation of the current research is that road freight is not included in the analysis of commuting. It would be interesting to focus on the travel patterns of those who work in the logistics sector, who spend time driving while working, given that the ATUS contains information on the mode of transport. Furthermore, we leave out of our analysis travel for other purposes, such as for leisure, personal care, or childcare responsibilities. Time spent on the road for these other purposes is not a negligible part of daily life, and it would be interesting to see how travel patterns change with fluctuations in gasoline tax rates. We leave this analysis for future research.

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Table 1
Summary Statistics of socio-demographic characteristics

Variables	(1)	(2)
Dependent variables	**Mean**	**Std. Dev.**
Commuting time	43.120	(39.910)
Proportion of commuting by private vehicle	91.61%	(25.510)
Proportion of commuting by public transport	2.70%	(14.270)
Proportion of commuting by physical mode	3.21%	(15.670)
Socio-demographic variables		
Male	0.549	(0.498)
Age	38.657	(12.893)
Hourly wage ($ per hour)	19.512	(15.490)
Education		
Less than 1st grade	0.002	(0.048)
1st, 2nd, 3rd, or 4th grade	0.008	(0.089)
5th or 6th grade	0.017	(0.129)
7th or 8th grade	0.015	(0.120)
9th grade	0.020	(0.139)
10th grade	0.024	(0.154)
11th grade	0.031	(0.173)
12th grade - no diploma	0.014	(0.116)
High school graduate - diploma or equiv.	0.287	(0.452)
Some college but no degree	0.177	(0.382)
Associate degree - occupational/vocational	0.045	(0.208)
Associate degree - academic program	0.048	(0.214)
Bachelor's degree (BA, AB, BS, etc.)	0.201	(0.401)
Master's degree (MA, MS, MEng, MEd, MSW	0.082	(0.274)
Professional school degree (MD, DDS, DV	0.015	(0.121)
Doctoral degree (PhD, EdD, etc.)	0.014	(0.118)
In couple	0.669	(0.471)
Spouse working	0.491	(0.500)
Number of children<18	1.229	(1.311)
Age youngest child	4.324	(5.436)
N. Observations	115,923	

*Notes:*Data come from the American Time Use Survey 2003-2015. Sample is restricted to workers who spend at least 60 minutes in market work activities, excluding commuting. Commuting time is calculated in minutes per day. Original survey weights are included in computations.

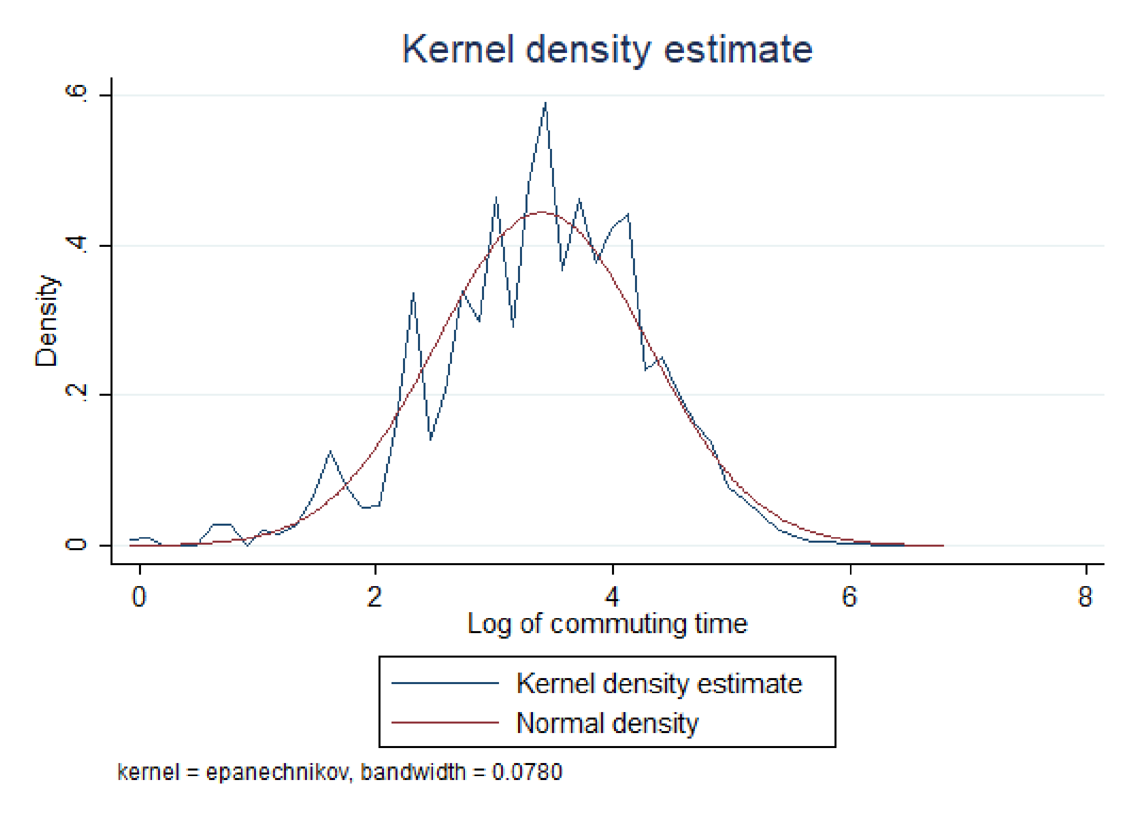
Table 2. Commuting time, proportion of commuting by mode of transport and gasoline tax rates

	(1)	(2)	(3)	(4)
	Total time	Percentage of commuting time		
	Commuting	Car	Public Transport	Physical mode
Gasoline tax rate	-0.079***	-0.353***	0.159***	0.255***
	(0.011)	(0.035)	(0.026)	(0.030)
Male	0.208***	-0.010	-0.018***	0.001
	(0.007)	(0.009)	(0.007)	(0.008)
Log age	0.101***	0.021	0.052***	-0.061***
	(0.012)	(0.017)	(0.012)	(0.014)
Log hourly wage	0.163***	0.055***	0.023***	-0.026***
	(0.006)	(0.009)	(0.006)	(0.008)
1st, 2nd, 3rd, or 4th grade	0.152**	-0.103	0.075	0.025
	(0.074)	(0.125)	(0.076)	(0.113)
5th or 6th grade	0.097	0.155	-0.052	-0.208**
	(0.068)	(0.109)	(0.063)	(0.100)
7th or 8th grade	-0.135*	0.110	-0.096	-0.123
	(0.070)	(0.110)	(0.061)	(0.103)
9th grade	-0.142**	0.139	-0.080	-0.130
	(0.068)	(0.108)	(0.062)	(0.101)
10th grade	-0.211***	0.165	-0.019	-0.247**
	(0.069)	(0.109)	(0.062)	(0.100)
11th grade	-0.175***	0.204*	-0.008	-0.299***
	(0.067)	(0.108)	(0.065)	(0.098)
12th grade - no diploma	-0.228***	0.205*	-0.149**	-0.175*
	(0.072)	(0.111)	(0.061)	(0.104)
High school graduate - diploma or equiv.	-0.164**	0.296***	-0.138**	-0.284***
	(0.065)	(0.103)	(0.057)	(0.097)
Some college but no degree	-0.167**	0.331***	-0.141**	-0.287***
	(0.065)	(0.103)	(0.057)	(0.097)
Associate degree - occupational/vocational	-0.113*	0.319***	-0.106*	-0.323***
	(0.066)	(0.104)	(0.059)	(0.097)
Associate degree - academic program	-0.070	0.340***	-0.157***	-0.325***
	(0.066)	(0.104)	(0.058)	(0.097)
Bachelor's degree (BA, AB, BS, etc.)	-0.086	0.222**	-0.077	-0.186*
	(0.065)	(0.104)	(0.058)	(0.097)
Master's degree (MA, MS, MEng, MEd, MSW	-0.153**	0.150	-0.023	-0.155
	(0.066)	(0.104)	(0.059)	(0.097)
Professional school degree (MD, DDS, DV	-0.128*	0.008	0.065	0.065
	(0.069)	(0.111)	(0.068)	(0.103)
Doctoral degree (PhD, EdD, etc.)	-0.227***	-0.001	-0.045	0.035
	(0.069)	(0.109)	(0.062)	(0.102)
In couple	0.074***	0.182***	-0.130***	-0.100***
	(0.011)	(0.016)	(0.012)	(0.013)
Spouse working	-0.080***	0.009	0.006	-0.019**
	(0.009)	(0.011)	(0.008)	(0.009)
Number of children<18	-0.013***	-0.005	0.010**	0.004
	(0.003)	(0.005)	(0.004)	(0.004)
Age youngest child	-0.002***	0.008***	-0.005***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Transport Performance Index	-0.015***	0.015***	-0.016***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-5.216***	6.352***	2.604	6.348***
	(1.743)	(2.294)	(1.604)	(1.947)
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	115,923	115,923	115,923	115,923
R-squared	0.065	0.022	0.02	0.016

Notes: Robust standard errors in parenthesis. Data come from the American Time Use Survey 2003-2015. Sample is restricted to workers who spend at least 60 minutes in market work activities. Columns (2), (3), (5), (6), (8) and (9) include dummy variables for the day of the week (ref.: Friday), and indicators to control for year and state fixed effects. The Transport Performance Index is obtained from the US Chamber of Commerce. Original survey weights are included in regressions. *Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level.

APPENDIX

Figure A1
Distribution of (log) commuting time



*Notes:*Data come from the American Time Use Survey 2003-2015. Sample is restricted to workers who spend at least 60 minutes in market work activities, excluding commuting. Original survey weights are included in computations.

Table 1. State gasoline tax rates, by state and year

STATE	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2011	2013	2014	2015
Alabama	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00
Alaska	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00
Arizona	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00
Arkansas	19.50	19.50	21.70	21.70	21.70	21.70	21.50	21.50	21.50	21.50	21.50	21.50	21.50	21.50	21.50	21.50
California	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	35.30	35.70	36.00	39.50	39.50	30.00
Colorado	22.00	22.00	22.00	22.00	22.00	22.00	22.00	22.00	22.00	22.00	22.00	22.00	22.00	22.00	22.00	22.00
Connecticut	32.00	32.00	25.00	25.00	25.00	25.00	25.00	25.00	25.00	25.00	25.00	25.00	25.00	25.00	25.00	25.00
Delaware	23.00	23.00	23.00	23.00	23.00	23.00	23.00	23.00	23.00	23.00	23.00	23.00	23.00	23.00	23.00	23.00
Dist. of Columbia	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	23.50	23.50	23.50	23.50	23.50	23.50	23.50
Florida	13.30	13.60	13.90	14.10	14.30	14.50	14.90	15.30	15.60	16.10	16.00	16.20	16.60	16.90	16.90	17.30
Georgia	7.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50	26.00
Hawaii	16.00	16.00	16.00	16.00	16.00	16.00	16.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00
Idaho	25.00	25.00	25.00	25.00	25.00	25.00	25.00	25.00	25.00	25.00	25.00	25.00	25.00	25.00	25.00	32.00
Illinois	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00
Indiana	15.00	15.00	15.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00
Iowa	20.00	20.00	20.10	20.10	20.30	20.70	20.70	21.00	21.00	21.00	21.00	21.00	21.00	21.00	21.00	30.80
Kansas	20.00	20.00	21.00	23.00	24.00	24.00	24.00	24.00	24.00	24.00	24.00	24.00	24.00	24.00	24.00	24.00
Kentucky	16.40	16.40	16.40	16.40	16.40	18.50	19.70	21.00	22.50	24.10	25.60	26.40	28.50	30.90	30.90	24.60
Louisiana	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00
Maine	19.00	19.00	22.00	22.00	25.20	25.90	26.80	27.60	28.40	29.50	29.50	29.50	30.00	30.00	30.00	30.00
Maryland	23.50	23.50	23.50	23.50	23.50	23.50	23.50	23.50	23.50	23.50	23.50	23.50	23.50	23.50	23.50	32.10
Massachusetts	21.00	21.00	21.00	21.00	21.00	21.00	21.00	21.00	21.00	21.00	21.00	21.00	21.00	24.00	24.00	24.00
Michigan	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00
Minnesota	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	22.50	27.10	27.50	28.00	28.50	28.50	28.50	28.50
Mississippi	18.40	18.40	18.40	18.40	18.40	18.40	18.40	18.40	18.40	18.40	18.40	18.40	18.40	18.40	18.40	18.40
Missouri	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00
Montana	27.75	27.75	27.75	27.75	27.75	27.75	27.75	27.75	27.75	27.75	27.75	27.75	27.75	27.75	27.75	27.75
Nebraska	23.90	24.50	24.50	24.60	24.80	25.30	27.10	27.00	26.00	26.40	27.10	26.30	26.20	26.30	26.30	26.10
Nevada	24.00	24.00	24.00	24.00	24.00	24.00	24.00	24.00	24.00	24.00	24.00	24.00	24.00	24.00	24.00	24.00
New Hampshire	19.50	19.50	19.50	19.50	19.50	19.50	19.60	19.60	19.60	19.60	19.60	19.63	19.63	19.63	19.63	23.83
New Jersey	10.50	10.50	10.50	10.50	10.50	10.50	10.50	10.50	10.50	10.50	10.50	10.50	10.50	10.50	10.50	10.50
New Mexico	18.50	18.88	18.88	18.88	18.88	18.88	18.88	18.88	18.88	18.88	18.88	18.88	18.88	18.88	18.88	17.00
New York	21.45	22.05	22.65	22.05	22.65	23.25	23.95	24.65	24.45	25.15	24.35	25.05	25.85	26.65	26.65	25.85
North Carolina	22.00	24.30	24.20	23.40	24.30	26.60	29.90	29.95	30.15	30.15	32.15	35.25	37.95	37.75	37.75	36.25
North Dakota	21.00	21.00	21.00	21.00	21.00	23.00	23.00	23.00	23.00	23.00	23.00	23.00	23.00	23.00	23.00	23.00
Ohio	22.00	22.00	22.00	24.00	26.00	28.00	28.00	28.00	28.00	28.00	28.00	28.00	28.00	28.00	28.00	28.00
Oklahoma	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00
Oregon	24.00	24.00	24.00	24.00	24.00	24.00	24.00	24.00	24.00	24.00	24.00	30.00	30.00	30.00	30.00	30.00
Pennsylvania	25.90	26.00	26.60	25.90	26.20	30.00	31.20	31.20	30.00	30.00	31.20	31.20	31.20	31.20	31.20	50.50

Rhode Island	29.00	29.00	29.00	29.00	30.00	30.00	30.00	30.00	30.00	30.00	32.00	32.00	32.00	32.00	32.00	33.00
South Carolina	16.00	16.00	16.00	16.00	16.00	16.00	16.00	16.00	16.00	16.00	16.00	16.00	16.00	16.00	16.00	16.00
South Dakota	22.00	22.00	22.00	22.00	22.00	22.00	22.00	22.00	22.00	22.00	22.00	22.00	22.00	22.00	22.00	30.00
Tennessee	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00
Texas	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00	20.00
Utah	24.50	24.50	24.50	24.50	24.50	24.50	24.50	24.50	24.50	24.50	24.50	24.50	24.50	24.50	24.50	24.50
Vermont	19.00	19.00	19.00	19.00	19.00	19.00	19.00	20.00	21.00	20.00	20.00	20.00	20.00	19.20	19.20	19.20
Virginia	17.50	17.50	17.50	17.50	17.50	17.50	17.50	17.50	17.50	17.50	17.50	17.50	17.50	11.10	11.10	16.20
Washington	23.00	23.00	23.00	28.00	28.00	31.00	34.00	36.00	37.50	37.50	37.50	37.50	37.50	37.50	37.50	44.50
West Virginia	25.35	25.35	25.65	25.35	25.35	27.00	27.00	31.50	32.20	32.20	32.20	32.20	33.40	34.70	34.70	34.60
Wisconsin	25.80	26.40	27.30	28.10	28.50	29.10	29.90	30.90	30.90	30.90	30.90	30.90	30.90	30.90	30.90	30.90
Wyoming	14.00	14.00	14.00	14.00	14.00	14.00	14.00	14.00	14.00	14.00	14.00	14.00	14.00	24.00	24.00	24.00

Notes: Gasoline tax rates are obtained from the Highway Statistics Series Publications, released by the Federal Highway Administration, US Department of Transportation (https://www.fhwa.dot.gov/policyinformation/statistics.cfm). Gasoline tax rates are measured in cents/gallon.

Table A2
Values of the Transportation Performance Index, by State

North Dakota	85.12	**Colorado**	61.52	**Wisconsin**	57.26
South Dakota	74.47	**Indiana**	61.32	**Louisiana**	56.37
Nebraska	71.66	**Arizona**	61.05	**Pennsylvania**	56.16
Montana	70.89	**Michigan**	60.67	**Arkansas**	55.52
Iowa	67.65	**Alabama**	60.48	**Florida**	55.26
Kansas	66.78	**Tennessee**	60.44	**New York**	55.19
Vermont	66.26	**South Carolina**	60.38	**Connecticut**	53.81
Maine	66.15	**Georgia**	59.72	**North Carolina**	53.39
Wyoming	65.56	**Ohio**	59.64	**New Mexico**	52.59
Minnesota	65.02	**Missouri**	59.6	**Massachusetts**	52.19
Oregon	64.72	**Kentucky**	59.51	**California**	51.76
Virginia	63.77	**New Hampshire**	59.48	**Nevada**	51.64
Utah	63.37	**Texas**	59.46	**Hawaii**	49.98
Idaho	63.06	**Maryland**	58.57	**New Jersey**	46.71
Alaska	62.7	**Illinois**	58.33	**Dist. of Col.**	35.08
Oklahoma	62.34	**West Virginia**	57.76		
Washington	62.06	**Delaware**	57.43		
Mississippi	61.68	**Rhode Island**	57.29		

Source: US Chamber of Commerce, 2011. States are ordered by decreasing order of the value of the *Transportation Performance Index*.