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Effects of Fuel Price Fluctuation on Individual CO_2 Traffic Emissions: Empirical Findings from Pseudo Panel Data

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Abstract

Globalized concerns about greenhouse gasses and increased energy consumptions have stimulated research in transportation about the relationships between fuel prices and emissions. Many researchers have found that higher fuel price can reduce fuel consumption and CO_2 emissions through a number of transmission mechanisms. However, most prior studies have been based on aggregate data and therefore do not reflect individual or household CO_2 adaptation behavior. Moreover, most studies have used cross-sectional data which inherently limit the study of dynamic effects. This paper therefore uses a pseudo-panel approach to estimate a dynamic model of transportation energy consumption and CO_2 emission. Seemingly unrelated regression analysis is used to reveal the interrelations between several dimensions of individual travel behavior such as the number of trips conducted, CO_2 emission, travel distance and fuel price. The results indicate that increasing fuel prices have negative effects on vehicle miles travelled, fuel consumption and CO_2 emissions, but positive effects on travel distance by public transport and slow modes.

Keywords: fuel price; CO2 emission; pseudo panel data

1. Introduction

Transport contributes more than one-fifth of global anthropogenic carbon dioxide emissions and over a quarter of emissions. Reducing energy consumption and eliminating energy wastage are among the main goals of the European Union (EU). The influence of various factors potentially affecting out-of-home energy consumption has been investigated extensively in previous studies. Many researchers have concluded that higher fuel price or

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trip costs may reduce fuel consumption and, therefore, CO_2 emissions through a number of transmission mechanisms (Han & Hayashi, 2008; Li, Linn, & Muehlegger, 2011; Lindsey, Schofer, Durango-Cohen, & Gray, 2011; Miles-mclean, Shelby, Lula, Sagan, & Francisco, 1992). In addition, past work has indicated that tele-working and telecommuting have a positive effect on energy consumption and CO_2 emissions (Choo, Mokhtarian, & Salomon, 2007; Jin & Wu, 2011; Yang, Arentze, & Timmermans, 2010).

Moreover, various demographic and socioeconomic factors have been found to contribute to a change in travel behavior and energy consumption, including age, gender, number of children and net-income (Bagley & Mokhtarian, 2002; Brazil & Purvis, 2009; Brownstone & Golob, 2009; Litman, 2012). These studies indicate that with increasing income and child ratio, VMT and CO_2 emissions tend to increase. Population age structure has also been found to have a significant influence on VMT but it varies across cohorts (Liddle, 2011). In addition, land use variables such as density and urban development have a significant influence on out-of-home energy consumption. Gómez-Ibánez & Humphrey (2010) found that compact development and mixed land uses result in less travel and energy consumption. Other studies found VMT to be lower in urbanized areas than in rural areas, and to be even lower closer to central business districts (Brownstone & Golob, 2009). The effect of transit availability and level of accessibility on VMT has also been documented in past studies (Graham & Noland, 2009; Litman, 2012).

While previous studies have investigated the effect of demographic and socioeconomic characteristics, land use, and fuel prices on VMT and energy consumption by car, the effect of fuel price or fuel tax on travel behavior by other transport modes, such as public transport and slow modes, has not been fully examined. For example, the use of alternative transport modes is expected to impact VMT and energy consumption, given the attributes of accessibility as well as the specific characteristics and perceptions of the owners of these vehicles. Moreover, most studies have been conducted at the aggregate level and therefore do not closely reflect individual and household CO_2 adaptation behavior which also inherently limits the study of dynamic effects.

Given the lack of studies on alternative transport modes, we used travel distance data by other transport modes of car drivers to analyze the substitution of driving by public transport or slow mode when fuel price is changing. Further, given the importance of dynamics for the problem at hand and the non-existence of panel data in the Netherlands, a pseudo-panel approach with travel information by different transport modes was used to estimate a dynamic model of transportation energy consumption and CO_2 emissions. To gain insight into this issue, this paper uses a seemingly unrelated regression approach to reveal the interrelations among travel distance by different transport modes, CO_2 emission, fuel price and socio-demographic characteristics. Energy consumption was determined using average fuel consumption (mpg) for three broad categories of transport modes (car, public transport and slow mode) used. The resulting numbers were then converted into CO_2 emissions.

The remaining part of this paper is organized as follows. The next section explains the structure of pseudo panel data set. Section 3 presents a conceptual framework related to out-of-home energy consumption behavior, used in this study. The seemingly unrelated regression used in this study is illustrated in Section 4. Results of model estimation are shown next. This study is concluded with a discussion about future research issues.

2. Construction of pseudo-panel data set

There is no recent panel data in the Netherlands about individual's activity-travel behavior, but there is a continuous national household travel survey that is carried out every year. Samples for these surveys are drawn anew each year, and thus it is impossible to track individuals over time. We therefore adopt a pseudo panel approach to track cohorts through such data. The concept of pseudo panel data was introduced by Deaton (1985). These data can be used in the absence of actual panel data to approximate the latter by following virtual persons over time and test for individual as well as dynamic effects.

Table 1 Overview of datasets

year	Birth year	Number of people in the sample	year	Birth year	Number of people in the sample
2004	1909~1986	38130	2007	1908~1989	29799
2005	1908~1987	33031	2008	1913~1990	23025
2006	1911~1988	29929	2009	1912~1991	23679

The pseudo panel data for this study was created using the 2004-2009 Dutch MON data (travel survey) on individual's activity-travel behavior. The survey covered each month from 2004 to 2009. An observation in this dataset is a daily diary based on trips conducted by household members. Besides household, individual, and transport mode ownership information, the survey also includes a single-day activity-travel diary.

The diary contains details about all trips made on the designated day and about the activities conducted at trip destinations, such as start time, end time, transport mode, type of fuel used, travel purpose, activity types, etc. Overall, this is a comprehensive data source for analyzing activity-travel behavior of Dutch residents. A brief overview of the datasets is given in Table 1. It consists of least 23,025 to most 38,130 valid household samples in each year, covering all provinces in the Netherlands.

A 'cohort' is defined as a group with fixed membership, individuals of which can be identified as they show up in the surveys. The most obvious example is year of birth. As a compromise between sufficient level of disaggregation and large enough cohort size, successive random samples of individuals from each of the cohorts were constructed. Three criteria were chosen:

- Year of birth (split up into 7 subgroups from 1908 to 1991): Group 1 1908~1928; Group 2 1929~1938;Group 3 1939~1948; Group 4 1949~1958; Group 5 1959~1968; Group 6 1969~1978; Group 7 1979~1991;
- Gender (0: male and 1: female)
- Types of fuel (0: petrol and 1: diesel and others)

The pseudo panel dataset contains 2016 cohorts. The distribution of the resulting cohort size is displayed in Fig.1. As can be seen, 1/4 of the cohorts is small with around 50 observations or below. However, these small cohorts contain relatively few of the total number of observations. Most cohort sizes are larger than 50 which is an acceptable size for analysis. The exogenous variables used in the model and their definition are shown in Table 2. The chosen seven variables are regularly used in models of travel behavior research (Brownstone, 2009; Weis & Axhausen, 2009). The average for those variables expected to have an impact on the mobility indicators were computed. Child ratio is included as a superior measure of household responsibilities when compared to the number of children. The reason for including it is that households with a higher child ratio are expected to make more trips as more household tasks need to be performed. Because information on fuel prices relevant to individual households is not available, national average price data were used. Fuel prices for diesel and petrol were derived from the energy publication website of AA (http://www.aaireland.ie). For this analysis, country-level, monthly average retail fuel prices in the Netherlands from 2004 to 2009 were obtained.

The key endogenous variables include the five endogenous variables provided in Table 3. They are CO_2 emission, energy consumption, vehicle miles travelled, travel distance by public transport modes and travel distance by slow modes.

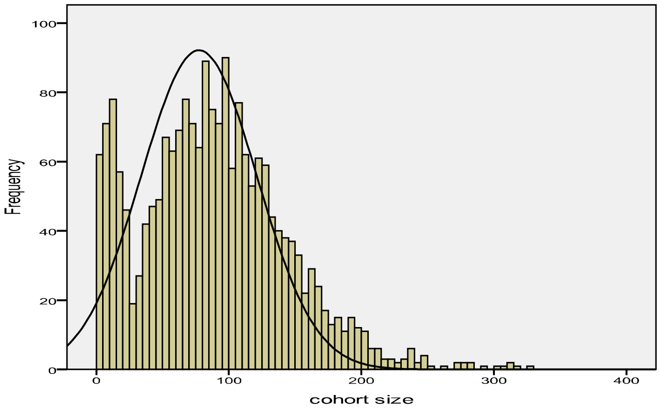

Fig. 1. Distribution of cohort size

Table 2. Exogenous variables

Name	Description	Type
A	Gender	Binary:0-men/1-woman
CR	Ratio of number of children under 18 to number of adults	continuous
HN	Number of people in household	continuous
I	Monthly personal net-income	continuous
Sted	Residential density in 5 levels	ordinal
p	Fuel price	continuous
TF	Type of fuel used	Binary:0-petrol/1-disesl

We obtained energy consumption data of vehicles in the Netherlands form CE Delft (Boer, Brouwer, & Essen, 2008). The data for vehicle energy consumption per kilometer cover both real-world average performance and specific technologies like emission classes, and fuels. Table 4 shows the details of energy consumption and CO_2 emissions for different transport modes.

To determine energy consumption and CO_2 emissions, travel distance was divided by the mpg of the transport mode used for that trip to calculate gasoline usage, which was then converted into energy use and CO_2 emissions. It should be mentioned that most tram/metro in the city use electricity as their energy supply. Although there is energy consumption for tram/metro, the CO_2 emission is almost equal to zero. Thus, we used 0 to present the CO_2 emission value of tram/metro.

Table 3. Endogenous variables

Name	Description	Type
CO2	CO_2 emission (g)	continuous
EC	Energy consumption	continuous
VMT	Vehicle miles travelled	continuous
TDP	Travel distance by public transport	continuous
TDS	Travel distance by slow mode	continuous

Table 4. Energy consumption and CO2 emission for different transport modes

travel mode	details	energy consumption (MJ/km)	CO2 emission (g/km)
Car	petrol	2,69	194,00
	diesel	2,42	180,00
Public transport mode	Bus	0,85	39,86
	tram/metro	0,52	0,00
	train	0,18	12,17
slow mode	bike/on foot	0,00	0,00

Source: CE Delft (Boer et al., 2008)

3. Model and approach

3.1. Energy consumption and CO_2 emission simultaneous equation system

In order to understand the possible interrelationship among travel distance by different transport modes, energy consumption and CO_2 emission, two hypothesized interrelationships among endogenous variables make up this framework. As shown in Fig. 2, the first hypothesis is an assumed relationship among travel distance by different transport modes. We assume that increasing travel distance by car tends to have a negative influence on travel distance by other transport modes. Moreover, as public transport is always connected with other transport modes and especially with slow modes, an increase in travel distance by public transport has positive effects on travel distance by slow modes.

The second hypothesis concerns the interdependencies between travel distance and energy consumption and CO_2 emissions. As shown in Fig. 3, we hypothesize that travel distance by car and travel distance by public transport have positive effects on both energy consumption and CO_2 emissions. However, increasing travel distance by slow modes will decrease energy consumption and CO_2 emissions.

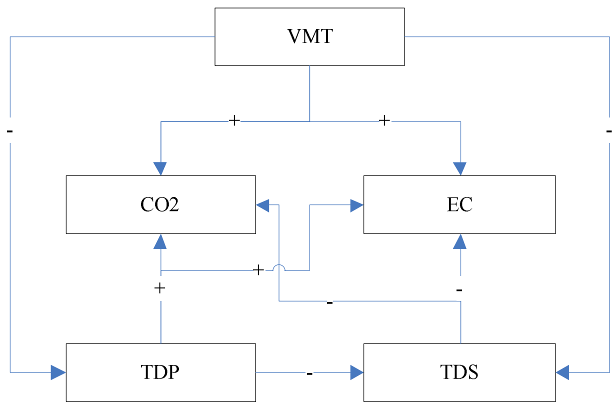

Fig. 2. Structure of simultaneous equation system

3.2. Simultaneous equation model

We begin by assuming that the endogenous variables: travel distance by different transport modes $D_{i,g,f,t}$, energy consumption $EC_{i,g,f,t}$ and carbon dioxide emission $CO2_{i,g,f,t}$ for cohort i with gender g in period t using f type of fuel can be expressed as a function of above exogenous variables.

$$D_{i,g,p,t}, EC_{i,g,p,t}, CO2_{i,g,p,t} = f(A_i, I_{i,g,f,t}, CR_{i,g,f,t}, HN_{i,g,f,t}, Sted_{i,g,f,t}, p_{f,t}, TF_{i,g,t}, G_i) \tag{1}$$

Where, $I_{i,g,f,t}$, $CR_{i,g,f,t}$, $HN_{i,g,f,t}$ and $Sted_{i,g,f,t}$ are personal net income per year, child ratio, number of household members and their living environment (urbanization per municipality) in cohort i . $p_{f,t}$ is the fuel price for f type of fuel in period t. All persons are assumed to face the same prices, so the fuel price varies only over time and is constant across individuals. $TF_{i,g,t}$ is the type of fuel for cohort i with gender g in period t. G_i is a cohort-specific generation effect, assumed to be the same for different gender and different fuel type user which is constant over time for each year-of-birth cohort.

Other differences in travel distance between cohorts are assumed to be randomly distributed and subsumed in the error term $u_{i,g,f,t}$. Considering the conceptual framework and assumptions made above, the endogenous variables of energy consumption and carbon dioxide emission in period t can be expressed as (2).

$$EC_{i,g,p,t}, CO2_{i,g,p,t} = f(I_{i,g,f,t}, CR_{i,g,f,t}, HN_{i,g,f,t}, Sted_{i,g,f,t}, p_{i,t}, TF_{i,g,t}, G_i) + u_{i,g,f,t} \tag{2}$$

Lags in adjustment of travel behavior endogenous variables are specified by a simple partial adjustment mechanism, so that travel distance by car in period t can be expressed as (3).

$$D_{i,g,p,t} = f(I_{i,g,f,t}, CR_{i,g,f,t}, HN_{i,g,f,t}, Sted_{i,g,f,t}, p_{i,t}, TF_{i,g,t}, G_i) + (1-\varphi)D_{i,g,f,t-1} + u_{i,g,f,t} \tag{3}$$

Considering the conceptual framework depicted in Fig. 3 and the equations mentioned above, we derive the following corresponding simultaneous equations (4) to (8).

$$VMT_{i,g,f,t}=f(I_{i,g,f,t}, CR_{i,g,f,t}, HN_{i,g,f,t}, Sted_{i,g,f,t}, p_{i,t}, TF_{i,g,t}, G_i)+(1-\theta)\times VMT_{i,g,f,t-1}+\alpha\times TDP_{i,g,f,t}+\beta\times TDS_{i,g,f,t}+\mu_{i,g,f,t}+\xi_1 \tag{4}$$

$$TDP_{i,g,f,t}=f(I_{i,g,f,t}, CR_{i,g,f,t}, HN_{i,g,f,t}, Sted_{i,g,f,t}, p_{i,t}, TF_{i,g,t}, G_i)+(1-\theta)\times TDP_{i,g,f,t-1}+\gamma\times TDS_{i,g,f,t}+\mu_{i,g,f,t}+\xi_2 \tag{5}$$

$$VMT_{i,g,f,t}=f(I_{i,g,f,t}, CR_{i,g,f,t}, HN_{i,g,f,t}, Sted_{i,g,f,t}, p_{i,t}, TF_{i,g,t}, G_i)+(1-\theta)\times TDS_{i,g,f,t-1}+\mu_{i,g,f,t}+\xi_3 \tag{6}$$

$$EC_{i,g,f,t}=f(I_{i,g,f,t}, CR_{i,g,f,t}, HN_{i,g,f,t}, Sted_{i,g,f,t}, p_{i,t}, TF_{i,g,t}, G_i)+\delta_1\times VMT_{i,g,f,t}+\delta_2\times TDP_{i,g,f,t}+\delta_3\times TDS_{i,g,f,t}+\mu_{i,g,f,t}+\xi_4 \tag{7}$$

$$CO2_{i,g,f,t}=f(I_{i,g,f,t}, CR_{i,g,f,t}, HN_{i,g,f,t}, Sted_{i,g,f,t}, p_{i,t}, TF_{i,g,t}, G_i)+\lambda_1\times VMT_{i,g,f,t}+\lambda_2\times TDP_{i,g,f,t}+\lambda_3\times TDS_{i,g,f,t}+\mu_{i,g,f,t}+\xi_5 \tag{8}$$

The coefficients of the model system were estimated using seemingly unrelated regression analysis. This method assumes that the error terms ξ are correlated across the equations. The results are shown in Tables 4 and 5.

4. Results

Based on the hypothesized relations discussed above, the causal structures of baseline model were specified. Fig. 3 and Table 5 show the estimated direct effects for the endogenous variables. As can be seen, all effects have the expected sign. The hypothesized effects except for effects of travel distance by slow mode on energy consumption and CO_2 emissions are all significant at the 5 per cent level.

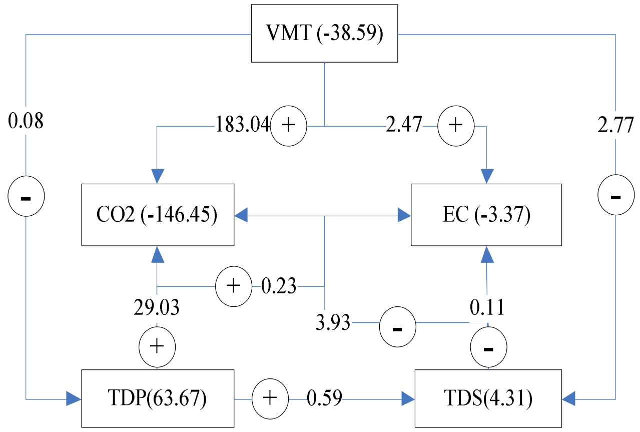

Fig. 3. Relation results among endogenous variables Signs in circles are a priori expectations on the direct effects; Numbers on arrows are coefficients resulting from model estimation; Numbers in rectangles are regression coefficients for fuel price

More specifically, travel distance by car has a strong negative effect on travel distance by slow mode, but a relatively small effect on travel by public transport. It indicates that public transport and slow mode are substitutions for car driving. Moreover, as expected, travel by public transport is more often connected with travel by slow mode. Further, as travel time per day is limited for each person, travelling more by car will have strong effects on energy consumption and CO_2 emissions. In contrast, travelling more by slow mode will reduce total energy consumption and CO_2 emissions. The results of exogenous effects are presented in Table 6. The five columns show the estimated coefficients for all five endogenous variables. All the estimated parameters have the expected signs and are generally significant at the 90% or 95% confidence interval. Adjusted R-squires are higher than 0.33

For exogenous variables, the estimated effects for each year of birth are shown from row 1 to row 5. These can be interpreted as lifecycle effects. The lifecycle effects exhibit the expected trends for all indicators. With increasing age, VMT, energy consumption and CO_2 emissions decrease, whereas travel distance by public transport increases. However, for travel distance by slow mode, the parameters of different cohorts do not show a progressively increasing/decreasing relationship between travel distance and age. The effect is generally increasing before g4 generation, indicating an increase in travel distance by slow mode for younger generations. It appears to fall after g3: the generation which is around 70 to 80 years old and travels most by slow mode.

Table 5. Direct effects among endogenous variables

		1	2	3	4	5
1	CO2 emission (g)			183.093**	29.028**	-3.975
2	Energy consumption			2.470**	0.238**	-0.108
3	Vehicle miles travelled					
4	Travel distance by public transport			-0.080**		
5	Travel distance by slow mode			-2.826**	0.574*	

* Variables significant at the 90% confidence interval.
**Variables significant at the 95% confidence interval.

Table 6. Effects of exogenous variables

Exogenous variables	Endogenous variables				
	1	2	3	4	5
g1	-173.266**	221.530**	-14.548**	-48.828**	-2725.914**
g2	-90.494*	159.011**	-3.437	-38.261**	-2276.896**
g3	-31.622	95.435*	0.377	-26.666**	-1648.835**
g4	-25.143	50.811	-0.993	-25.541**	-1466.895**
g5	-11.819	22.771	-2.431**	-7.793**	-434.167
Gender	0.035	-4.134**	0.326**	0.470	31.874
Child-ratio	-60.869	-124.493**	-5.812**	-62.844**	-3229.315**
Household number	10.765	81.911**	5.537**	23.565**	1120.510**
Net-income value	0.010**	-0.002**	-0.000**	-0.001**	-0.041**
Urban density	47.524**	-5.621	1.705**	-6.877**	-246.877
Type of fuel	59.717**	28.747**	2.624**	-106.131**	-5512.668**
Fuel price	-21.994	60.727**	4.293**	-3.250	-139.257
VMT(-1)	0.339**				
TDP(-1)		0.348**			
TDS(-1)			0.289**		
Adjusted R-squared	0.606	0.373	0.331	0.996	0.996

* Variables significant at the 90% confidence interval.
**Variables significant at the 95% confidence interval.

As for socio-demographic parameters, the parameter for child-ratio is negative for all indicators, which indicates that individuals with more children are less mobile. However, the parameters for household size are positive for almost all indicators, which indicate that individuals from large households have more need to travel and consume more energy. Moreover, the parameters for net-income indicate that individuals who earn a high salary usually drive larger distances, and use less public transport and slow modes. However, the effects are small. To our surprise, they consume less energy and have lower CO_2 emissions. Upon closer inspection, we found the existence of a significant positive relationship between income and type of car, suggesting that individuals who earn a high salary tend to disproportionally have more diesel than petrol cars which consume less energy and produce fewer emissions. For the other socio-demographic parameter- residential density, we find that density directly influences vehicle usage, and both density and usage influence fuel consumption and CO_2 emissions. Individuals who live in rural areas drive more often than others. However, they also travel more by slow mode, which may explain why they consume less energy and have lower CO_2 emissions.

As far as energy type and fuel price are concerned, the effects of energy type show that individuals with diesel car driver more and meanwhile use other transport modes more than petrol car users do. Since diesel cars consume less energy and release less CO_2, it has significant negative effects both on energy consumption and CO_2 emissions. As shown in Table 6, generally speaking, increasing fuel price has significant negative effects on VMT, energy consumption and CO_2 emissions, but positive effects on travel distance by public transport and slow mode. Moreover, the impact of fuel price on travel distance is different for different transport modes. For instance, fuel price has the strongest impact on travel distance by public transport. Increasing prices coincide with increasing travel distance by public transport.

Finally, the parameters of the lag effects show how travelers adjust to changes in fuel prices. The adjustment parameter for VMT and TDP indicates that almost 66% of the adjustment of VMT and TDP to changes in the independent variables occurs within one month. In contrast, the percentage is 71% for slow modes.

5. Conclusion and discussion

The results presented in this paper illustrate the usefulness of the pseudo-panel methodology in analyzing dynamic relationships among mobility, energy consumption and CO_2 emissions. The results obtained confirm the hypothesized relationships among the five indicators. Increase in fuel price is found to reduce travel distance by car, and to increase travel distance by other transport modes, especially by public transport.

Equally interesting are the cohort effects. The results imply that the younger generation use more private transport modes than the older generations, consuming more energy. It also indicates that improvement of vehicle technology did not stop the trend of increasing energy consumption and CO_2 emissions.

Some limitations of the present study should be mentioned. First, the fuel price data used in the current study represent an average for the Netherlands, and therefore these data do not reflect local differences. Second, the MON data pertain to a particular day, whereas the fuel price data concern a monthly average. This means that any within-month variability in the fuel price data is not captured in the model estimation.

This research can be usefully extended in a number of directions. Future studies could explore how hypothetical changes in fuel tax and density would affect passenger VMT, public travel distance and travel distance by slow modes, and analyze the corresponding impacts on future energy consumption and GHG emissions. It would be also interesting in future research to apply uncertainty analysis to these uncertain input data and examine to what extent the model outcomes are influenced by the degree of uncertainty in these input data.

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