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An integral evaluation of dieselisation policies for households' cars

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ABSTRACT

Reducing energy consumption and CO_2 emissions in the transport sector is a priority for Great Britain and other European countries as part of their agreements made in the Kyoto protocol and the Voluntary Agreement. To achieve these goals, it has been proposed to increase the market share of diesel vehicles which are more efficient than petrol ones. Based on partial approaches, previous research concluded that increasing the share of diesel vehicles will decrease CO_2 emissions (see Al-Hinti et al., 2007; Jeong et al., 2009; Zervas, 2006). Unlike these approaches, I use an integral approach based on discrete choice models to analyse diesel vehicle penetration in a broader context of transport in Great Britain. I provide for the first time, empirical evidence which is in line with Bonilla's (2009) argument that only improvements in vehicle efficiency will not be enough to achieve their goals of mitigation of energy consumption and CO_2 emissions. The model shows the technical limitations that the penetration of diesel vehicles faces and that a combination of improvements in public transportation and taxes on fuel prices is the most effective policy combination to reduce the total amount of energy consumption and CO_2 emissions among the analysed dieselisation polices.

1. Introduction

Great Britain along with other European countries needs to design policies to reduce the amount of emissions of carbon dioxide (CO_2) and other pollutants as part of their obligations acquired in the Kyoto protocol and the Voluntary Agreement for the European Union (EU). The transport sector contributes 30% of the total CO_2 emissions and it accounts for 60% of the total oil consumption in the OECD countries.[2] For this reason policy makers and researchers believe that more CO_2 emissions can be saved from the transport sector. Nevertheless there is no agreement about the mechanism that can lead to reduced energy consumption and CO_2 emissions.[3] One of the strategies to achieve these goals is to increase energy efficiency in the sector. For this reason increasing diesel vehicles has been proposed as a strategy given that these vehicles are more efficient than the petrol ones. However, it is important to mention that reducing CO_2 emission is not the only relevant goal that the transport sector aims to achieve. With regard to this, Bonilla (2009) pointed out that even when the average fuel efficiency is improved, environmental problems can be aggravated. For example diesel cars are more efficient than petrol ones but they have also a higher emission of particulates which are another dangerous form of pollution.

According to Bonilla (2009), increasing the share of diesel vehicles in Great Britain and therefore the average fuel economy[4] is achievable only in the long run and can be driven by income and car prices. In the case of Korea, Lee and Cho (2009) estimate the future demand of diesel vehicles, finding that consumers would increase the demand of those vehicles if the price of diesel were relatively cheaper than petrol. Kim et al. (2006) found that changes in diesel price can be an effective policy to make changes in the share of diesel vehicles in the total vehicle stock. It is unclear however, if only increasing the number of diesel vehicles can solve the problem of reducing energy consumption and the mitigation of green house gases. Regarding this, Al-Hinti et al. (2007) found that increasing the number of diesel cars in Jordan's economy reduced the amount of energy consumption and CO_2 emissions. Jeong et al. (2009) analysed the effect of introducing diesel vehicles in the Korean economy. They found that increasing the number of diesel vehicles has decreased carbon emissions but it also has increased the general amount of pollutants. Similar results were found for Ireland by Zervas (2006).

On the other hand, based on analysis of improvements in the efficiency of new vehicles in the UK, Bonilla (2009) concluded that it is likely that the EU environmental agreements will not be

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[1] I am grateful to two referees and Dr. Emma Iglesias for their helpful comments. All the remaining mistakes are my own. A version of this paper was presented in the 3er ELAEE conference.

[2] See OECD Annual Report 2009. www.oecd.org/dataoecd/38/39/43125523.pdf.

[3] See Schipper (2009).

[4] The average fuel economy is the average of the ratio between distance travelled and energy consumed.

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reached given that these improvements are not sufficient. The fact that improvements in energy efficiency fail to reach their goals can be attributed to a *rebound effect*. According to Frondel et al. (2007) having more efficient vehicles can make energy use cheaper and therefore it can increase its consumption. Similarly Schipper and Fulton (2009) noted that the *rebound effect* can have three sources: (1) an increase in the number of diesel cars as a result of petrol drivers switching to diesel cars to drive more, (2) an increase in the intensity of using diesel cars from owners who already own these vehicles, and (3) an increase in the number of bigger and heavier vehicles. Moreover, Schipper et al. (2002) argue that on average a decrease in 10% of the price of travelling could induce an increase in the demand of travelling of 5% (i.e. an elasticity of 0.5). However, they argued that in Europe this effect can be higher given that commuters have more flexibility to switch from public transportation to car when the price of travelling by car is reduced.

The demand of diesel cars tend to be focused on big vehicles and as noted by Cuenot (2009) there is a correlation between weight and CO_2 emissions, and therefore possible gains coming from fuel efficiency can be offset by the weight of diesel vehicles. Bonilla and Foxon (2009) found that people with high income tend to buy larger diesel cars which increases fuel consumption. In the same vein, Schipper and Fulton (2009) noted that there is a self selection process in the purchase of diesel vehicles.[5] Moreover, they argued that it is important to identify the determinants of this process given that they play also an important role in the use of these vehicles. Therefore, how to introduce more efficient vehicles in the economy is still an unanswered question. Moreover, modelling dieselisation of the vehicle stock requires an integral approach that allows the evaluation of improvements of efficiency and changes in commuter preferences in a broader context of transport. In this sense, all previously mentioned studies visualise diesel vehicle penetration as an isolated phenomenon, and therefore this limits the analysis. The objective of this paper is to improve the modelling approach providing an integral analysis that will bring new evidence of the effect of improving the average fuel efficiency on energy consumption and CO_2 emissions by an increase in the number of diesel vehicles. Moreover, the model is able to analyse different dieselisation policies based on changes in fuel prices and improvements of public transportation.

Integral approaches have been used by Mohammadian and Miller (2003) to estimate vehicle ownership and type of vehicle decision. More recently Chiou et al. (2009) analysed changes in energy and emissions based on integrated model that follows a "bottom up style" where several modules such as vehicle ownership, type of vehicle and usage are linked through technical principles to estimate changes in energy consumption and emissions. The model was applied to a Korean survey that was carried out in 2006. While their objective was not to analyse diesel vehicle penetration, this structure allowed them to have a broader vision of the effects that changes in preferences of drivers for different car type models and usage have on energy consumption and green house emissions.

In this paper, diesel vehicle penetration is analysed by expanding Chiou et al's. (2009) model to be applied to a repeated cross section dataset that allows the study of changes across time. Unlike Chiou et al. (2009), the model proposed here comprises two additional modules. One for travel mode to analyse commuter's behaviour and other for newly acquired vehicles. This allows the effects on energy consumption and CO_2 emissions of improvements in public transportation to be included. In addition, the ownership module is estimated in a two stage approach. This structure allows analysis of the effect of improvements in public transportation along with changes in diesel vehicle penetration on energy consumption and CO_2 emissions. However, given limited information about usage and efficiencies of other transport modalities, the model estimates *only* energy consumption and CO_2 emission coming from households' cars.[6] My model also distinguishes *Big cities* from the rest of Great Britain to analyse possible regional effects. The estimation is based on the National Travel Survey (NTS) for the case of Great Britain from 1998 to 2006. The NTS carries out a survey of household transport behaviour in the UK. The dataset reports information in different dimensions such as transport mode, vehicle type and usage choice.

The model shows evidence that diesel vehicle penetration faces technical limitations given that these vehicles are more likely to be purchased by male consumers with high income and with preferences for heavy vehicles. Therefore manufactures face a double challenge: they need to make these vehicles lighter and accessible to different kind of driver regardless of gender or socioeconomic level and at the same time improve fuel efficiency. Moreover the model provides empirical evidence that increasing the number of diesel cars by either a reduction in diesel price or an increase in diesel fuel efficiency does not decrease energy consumption or CO_2 emissions. This effect is attributed to fact that these policies also increase the usage of diesel vehicles prompting a *rebound effect* as found by Frondel et al. (2007) and Schipper and Fulton (2009). Therefore, in contrast to Al-Hinti et al. (2007), Jeong et al. (2009), and Zervas (2006), increasing the diesel vehicle penetration alone will not provide mitigation effects on energy consumption and CO_2 emissions. These findings support Bonilla (2009)'s argument that increasing the number of diesel vehicles will not be enough to achieve Great Britain's environmental compromises. Nevertheless the combination of introducing vehicle efficiency via taxing petrol cars along with improvements in public transportation induces the highest reduction in energy consumption and emissions of CO_2 from households' cars.

My model presents several advantages over partial approaches and studies based on time series techniques. Vaage (2000) argued that time series techniques use aggregate data that omits many important characteristics of households. Consequently this can lead to missing variables and potentially, to mis-specification bias. In addition, aggregate results do not allow authorities to evaluate the effect of policies across households. This paper overcomes these problems using cross section data combined with discrete choice models. In addition, the model provides as far as I know the first empirical evidence of the effects of different dieselisation policies based on a very tractable structure that allows analyses of different aspects of the transportation sector.

The paper comprises five sections. Section 2 describes the econometric techniques used and the details of how the modules are linked. The subsequent two sections explain the dataset used and the econometric results. The forth and the fifth sections provide the results of the policies experiments and conclusions, respectively.

2. The model and methodology

2.1. The general structure

The model is a modular estimation that comprises five modules linked through technical factors. The first module estimates

[5] The authors argue that given that the cost for diesel cars is higher than for petrol ones, purchasers have an idea of the number of miles that they have to drive to make the investment profitable when they buy a diesel car.

[6] The structure of the model makes it possible to estimate energy consumption and CO_2 emission from other modalities of transportation provided that the information is available.

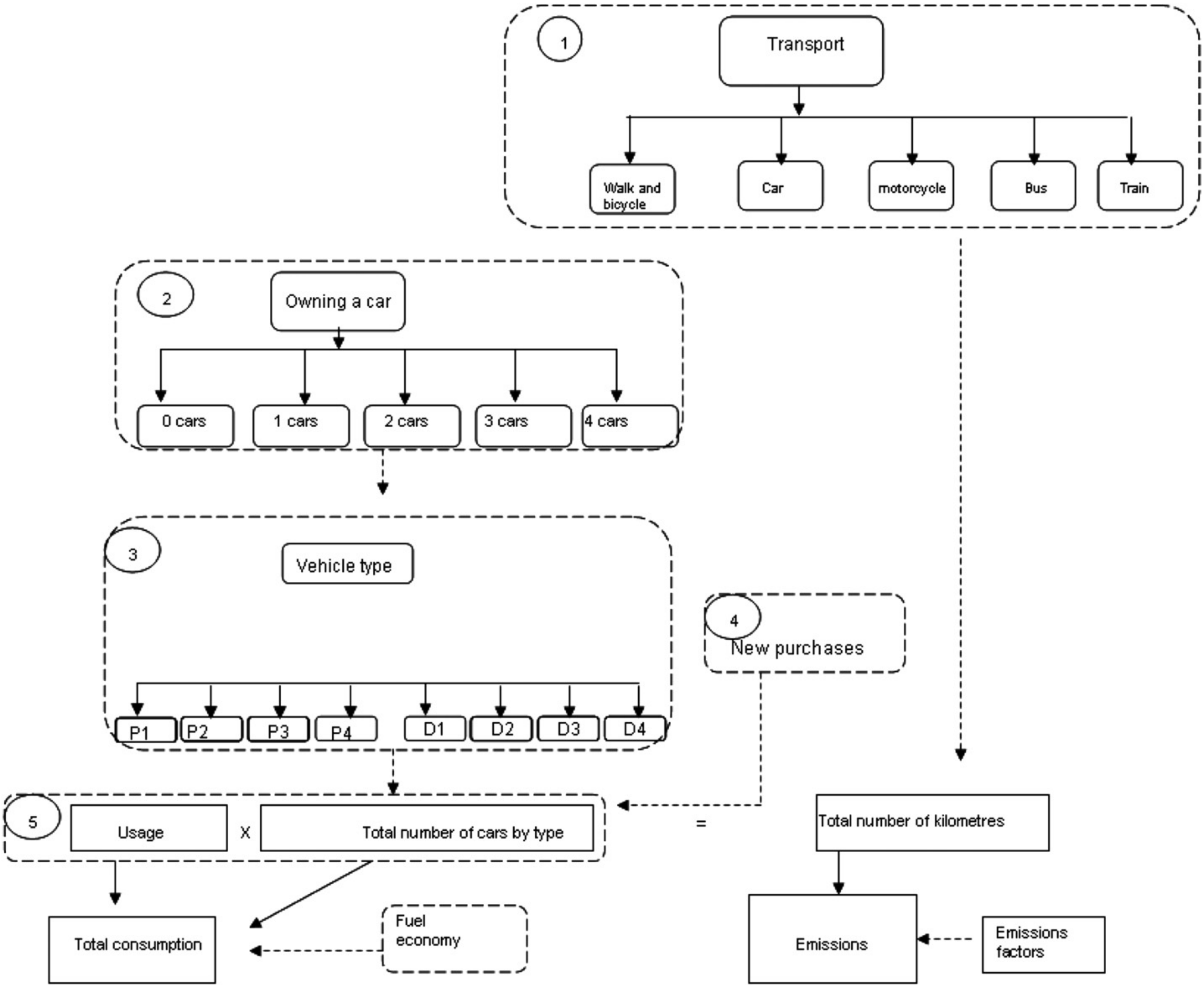

Fig. 1. Integrated structure.

the elements that determine the commuter's decision for transport mode, from now on denoted as $m1$. Module 2, estimates the household's decision of how many cars to own ($m2$). The third module analyses the individual decision of vehicle type ($m3$), while $m4$ estimates changes in the vehicle stock, and finally module 5 ($m5$) estimates the annual kilometres that vehicles are used. The model structure is shown in Fig. 1.

Chiou et al. (2009) estimate the sensitivity of commuters to changes in transport cost using a stated preference methodology[7]; however, the NTS dataset is not designed to allow for this kind of estimation. Therefore $m1$ is added to estimate the sensitivity of commuters to changes in transport modes prices. This fact, unlike Chiou et al. (2009), allows the model to accommodate for changes in prices and other factors that determine commuters' decisions about mode of travel.

In the second module ($m2$) the total number of vehicles is estimated based on the total number of British households and the probability of vehicle ownership. The total number of vehicles is disaggregated using Multinomial Logistic Models estimated in $m3$. It provides the shares needed to disaggregate the vehicle stock by fuel and age. New purchases of vehicles are estimated in module 4 using an ordered probit model. Finally, the intensity of vehicle usage is estimated in $m5$ where the annual kilometres can be disaggregated by type and age of vehicle. Once the number of vehicles per different categories is multiplied by the annual kilometres, it is straight forward to estimate energy consumption and emissions. This is carried out using the average amount of fuel consumption per kilometre and emission factors provided by the Department of Transport.[8] Emission factors are broken down by vintage, fuel and engine capacity and therefore real shares taken from the NTS are used to disaggregate the vehicle stock at engine capacity level.

To introduce changes in commuter preferences, changes in $m1$ are transmitted to the model by the ratio of probabilities of

[7] According to Azevedo et al. (2003), revealed preferences estimation is based on factual information while a stated preferences one is based on the possible reaction of demand to hypothetical changes in prices.

[8] Tables 1 and 3 show factors of efficiency and emissions used in this estimation. These estimates are available at http://www.dft.gov.uk/pgr/statistics/datatablespublications/energyenvironment/ and http://www.dft.gov.uk/pgr/roads/environment/emissions/.

travelling by car, where p_{car}^{m1} is the probability that an individual chooses to travel by car in region h at time t and it is estimated in $m1$. In $p_{car}^{m1}(1)/p_{car}^{m1}(0)$ the base scenario (0) and an alternative scenario (1) are compared. The alternative one represents, for instance, changes in prices of public transportation via subsidies. More details are provided in the next sections.

2.2. Mode transport module

The first module $m1$, presents five options for commuters: walking, bicycle, car, motorcycle, bus and train. The estimation of p_{carht}^{m1} is carried out using a Conditional Multinomial Logit model (*CML*). The model is interpreted in the framework of Random Utility Models (RUM). The model follows the next specification where for simplicity the subscript for individuals is omitted:

$$U_{jht} = x_{jht}^{m1'}\beta^{m1} + z_{ht}^{m1'}\gamma_j^{m1} + \varepsilon_{jht}^{m1}, \tag{1}$$

where U_{jh} is the utility for alternative j in region h at time t which is not observable. Moreover, x_{jt}^{m1} is the vector of alternative-specific variables while z_{ht}^{m1} comprises the case-specific variables. Therefore, the probability of choosing alternative j in region h at time t is estimated by

$$p_{ht} = \frac{\exp(x_{jht}^{m1'}\beta^{m1} + z_{ht}^{m1'}\gamma_j^{m1})}{\sum_{l=1}^{J}\exp(x_{lht}^{m1'}\beta^{m1} + z_{ht}^{m1'}\gamma_l^{m1})}, \tag{2}$$

and $j=1, \ldots J$, $t=1, \ldots, T$, and $h=1, \ldots, H$. In this framework, the error terms ε_{jht}^{m1} are assumed to be independent and identically distributed (*iid*). Therefore, when an individual is comparing two alternatives, the addition of a new one does not affect the distribution of the probability that the individual attributes to the two initial alternatives. That is, ε_{jht}, does not contain any alternative-specific unobservable information.

The previous property is technically called the Independence from Irrelevant Alternatives (IIA). In some situations this property cannot be a realistic representation. Nevertheless, it can be relaxed assuming that ε_{jht} can be correlated across alternatives. Ben-Akiva (1974) introduced a Nested Multinomial Logit (*NML*) that relaxes the IIA assumption. In $m1$ commuters face a two levels tree of decision. In the first level, commuters choose between travelling by non motorised mode, private motorised and public motorised which are called limbs j by Cameron and Trivedi (2009) while the elements that belong to each limb are called branches denoted as k. The first nest or branch comprises the choices walking and cycling, the second one car and motorcycle and the third one bus and train. In this structure the probability that a commuter in region h at time t travels by car is denoted as p_{21ht}. Subscript 21 denotes second limb (private motorised) and first choice (car) in the branch. The probability of choosing an alternative k within a branch that belong to limb j is estimated as follows:

$$p_{jkht} = p_{jht}p_{k/jht} = \frac{\exp(v_{jht}'\alpha + \tau_j I_{jht})}{\sum_{n=1}^{j}\exp(v_{nht}'\alpha + \tau_n I_{nht})} \times \frac{\exp(x_{jkht}'\beta_j/\tau_j)}{\sum_{l=1}^{k}\exp(x_{jlht}'\beta_j/\tau_j)}, \tag{3}$$

where the vector v_{jht} comprises all the variables that only varies across individuals, limbs region and time while the vector x_{jkht} comprises the variables that vary across all the subscripts. Note that x_{jkht} in this procedure and x_{jht}^{m1} in the *CML*, contains the same information the only difference is that in the nested method the elements of x_{jht}^{m1} are divided into k groups.

The variable I_{jht} is the inclusive value. The economic intuition is that once the individuals choose the alternative at the bottom level, then the information of this utility is brought back to the highest level through the inclusive value. It is defined as

$$I_{jht} = \ln\left[\sum_{l=1}^{k_j}\exp(x_{lht}'\beta_j/\tau_j)\right]. \tag{4}$$

Moreover, τ_j is called the dissimilarity parameter and its value must be between zero and one. $1-\tau_j$ will provide information about the correlation across alternatives in a nest.[9] Following Chiou et al. (2009) methodology, when τ_j is found to be out of its range, then a conditional logit model is used instead. A caveat of logit models is the assumption of proportionality in the pattern of substitution. Possible alternatives are Multinomial Probit models and Cross-Nested logits which can capture flexible patterns of substitution. However, when either the dataset or the number of alternatives is very large, as in my estimation of transport mode and vehicle type, estimation of the parameters become a computational burden. As noted by Chiou et al. (2009), the estimation of the parameters using those models can be extremely severe under these circumstances.

2.3. Ownership module

The UK vehicle ownership has been analysed by Dargay and Hanly (2004b) applying ordered probit models. Their strategy was to estimate the probability of owning s vehicles where s takes values from zero to three. The authors used the British Panel Survey which does not include any variable of vehicle price and therefore it was needed either to impute zero prices or allowing for missing values for the households that own zero vehicles. Even though in their paper it is not explicit the way that the problem was solved, according to Frondel and Vance (2010) in this situation a two stage procedure is more appropriate given that there is a sample selection problem. In the first step a probit model is estimated to control for the sample selection problem prompted by the zero cases.

In this paper I follow Frondel and Vance (2010) philosophy where in the first step a probit model is estimated to compute the probability of being a vehicle owner. For the second stage, instead of estimating another model for the number of vehicles owned by households I use real actual shares for owning s cars, where $s=1$, 2,3 or more vehicles. The product of the probabilities obtained from the first stage and these shares provide an estimate of p_{sht}^{m2}. Therefore for the first stage $U_{ht}^{m2} > \overline{U_{ht}^{m2}}$ if household in region h at time t owns a car. Where U_{ht}^{m2} and $\overline{U_{ht}^{m2}}$ denote the utility of car owners and non car owners. Therefore, the probability is estimated as follows:

$$\Pr(U_{ht}^{m2} > \overline{U_{ht}^{m2}}) = F(x_{ht}^{m2'}\beta), \tag{5}$$

where $F(*)$ is a cumulative distribution function for the error terms. The most common functions are the normal and logistic. When the normal function is specified the model is called probit. The predicted probabilities from both models are very similar. However, for a self selection stage it is very common to find in the literature the use of probit models.[10] Therefore, I use a probit model for the policy evaluation section.[11] Consequently, for the second decision, real shares from the NTS are used as follows:

$$p_{sht}^{m2} = \Pr(U_{ht}^{m2} > \overline{U_{ht}^{m2}}) \times Shares\ \ of\ \ owning\ \ s\ \ cars \tag{6}$$

with this specification changes in $Pr(U_{ht}^{m2} > \overline{U_{ht}^{m2}})$ will modify the probability of owning s vehicles in region h at time t.

[9] See Train (2003).

[10] See Heckman (1979) and Frondel and Vance (2010).

[11] Cameron and Trivedi (2005) note that the estimated probabilities from logit and probit models are very similar.

2.4. Vehicle type and availability

This module estimates the probability of choosing a car type g in region h at time t denoted as p^{m3}_{ght}. As shown in Fig. 1, this module is designed to give individuals eight choices of vehicles. The choices are a result of the combination of different car type models and fuel type. The car type models options are as follows: up to 1 year, from 1 to 3, from 3 to 5, and over 5 while the fuel choices are either petrol or diesel vehicles. The estimation is carried out using *CML* and *NML* models as in module 1 following expressions (2) and (3). Nevertheless, in this module the decision tree that drivers face has two limbs, one for petrol and other for diesel vehicles. The branches in each limb represent different choices of car type models.

On the other hand, to estimate the new purchases of vehicles the NTS provides information about the *vehicle availability* recorded in three answers: (1) vehicle in regular use, (2) possibly will come into use, and (3) newly acquired vehicle. The last answer is particularly interesting given that I can estimate the changes in the probability of buying a diesel car given changes in either fuel or car prices of those vehicles. Therefore, the individual's answer to the question of *vehicle availability* can be seen as the utility that the individuals attribute to each answer according to their ratings (see e.g. Train, 2003). Consequently, the probability that an individual chooses alternative a (i.e. the values that *vehicle availability* takes) for vehicle type g is estimated using an ordered probit model.

I assume that the unobservable utility function denoted as U^{m4*}_{ght} is contained in the interval $(\eta_{a-1},\eta_a]$, where η_{a-1},η_a are threshold values. Therefore the probability that households choose alternative a is given by

$$\Pr(U^{m4}_{ght}=a_{gh})=\Pr(\eta_{a-1}<U^{m4*}_{ght}\le\eta_a)=P(U^{m4*}_{ght}\le\eta_a)-P(U^{m4*}_{ght}\le\eta_{a-1})$$

$$=F(\eta_a-x^{m4'}_{ght}\beta^{m4})-F(\eta_{a-1}-x^{m4'}_{ght}\beta^{m4}),\quad a=1,2,3, \tag{7}$$

where x^{m4}_{ght} comprises all the independent variables such as fuel and car prices and household's characteristics. $F(*)$ is the cumulative distribution function of the error terms. This function can be specified to be logistic or normal. If it is specified as normal, the model used is called probit. However note that the logit model unlike the probit assumes independency between the error terms and the alternatives. Consequently this assumption cannot be realistic given the ordered nature of the variable *vehicle availability*.[12] Therefore the predicted probabilities are estimated by a probit model in the simulation experiment.

2.5. Energy consumption and emissions

The total number of households that own s vehicles at time t in region h is estimated by the following expression:

$$NH_{sht}=(p^{m2}_{sht}N_{ht}), \tag{8}$$

where N_{ht}[13] is the total number of households in region h at time t.

Once this decision is made, commuters can choose the kind of car that they want to buy. Fig. 1 shows that they can choose two general options: petrol or diesel vehicles for different car type models. The probability of choosing a vehicle of type g in region h at time t is denoted as p^{m3}_{ght}. It is estimated using *CML* and *NML*. To compute the number of vehicles of type g in region h at time t (i.e. TV_{ght}), first the total number of vehicles TV in region h at time t are estimated as follows:

$$TV_{ht}=\sum_{s=1}^{4}NH_{sht}\,s, \tag{9}$$

where s takes values from 1 to 4 denoting the number of cars that households can own. TV_{ght} is computed by expression (10) as follows:

$$TV_{ght}=TV_{ht}\,p^{m3}_{ght}, \tag{10}$$

where p^{m3}_{ght} is the probability of owning a car type g in region h at time t estimated in $m3$. Moreover $g=1,2,\ldots,G$.

The introduction of new vehicles is estimated in module 4 by expression (7), particularly by changes in the probability for newly acquired vehicle. Therefore under an alternative scenario (i.e. a reduction of diesel price), TV_{ght} is multiplied by the difference in expression (7) with respect to the base scenario as follows:

$$TV_{ght}(1+\Delta Pr(U^{m4}_{ght}=\text{newly acquired vehicles})),$$

where $\Delta\Pr(U^{m4}_{ght}=\text{newly acquired vehicles})$ is the change in the probability of new acquired vehicle for a given change in fuel or car prices.

Regarding the annual kilometres that vehicle g is used (i.e. $usage_{ght}$), it is estimated in module 5 by the following expression:

$$\ln Y_{ght}=X^{m5}_{ght}\beta^{m5}+\varepsilon_{ht}, \tag{11}$$

where $\ln Y_{ght}$ is the logarithm of the annual kilometres of an individual in region h at time t of the g type, ε_{ght} is the error term and X^{5m}_{ght} is the matrix with all the independent variables. More specific details of the variable used in the estimation are provided in the next section. The model is estimated by Pooled Ordinary Least Squares (POLS). Note that $usage_{ght}$ is estimated as the exponential function from (11).

On the other hand, the total kilometres (i.e. TM_{ght}) by car type g in region h at time t is estimated by the following expression:

$$TM_{ght}=TV_{ght}usage_{ght}\frac{p^{m1}_{carht}(1)}{p^{m1}_{carht}(0)}, \tag{12}$$

where $p^{m1}_{carht}(1)/p^{m1}_{carht}(0)$ measures the proportion of change in the probability of travelling by car estimated in $m1$. It compares the scenario base (0) and the scenario of changes in bus prices (1). Note that in the base scenario $p^{m1}_{carht}(1)/p^{m1}_{carht}(0)=1$. Fuel consumption and emissions are estimated as follows:

$$FV_{ght}=TM_{ght}/efficiency_{gt}, \tag{13}$$

where $efficiency_{gt}$ is the fuel average consumption per mile in g category at time t.

The amount of CO_2 emissions in region h at time t is computed by the following expression[14]:

$$CO_{2ght}=TM_{ght}\,emission\ \ factors \tag{14}$$

3. Empirical results

3.1. The dataset

The dataset is provided by the National Travel Survey (NTS) and it comprises information at individual, household and vehicle level. The data is generated by an annual survey carried out in the United Kingdom. However, in this research only the case of Great Britain is analysed. Moreover, only information of individuals

[12] See Train (2003).

[13] See Table 1 for details on the number of households.

[14] The emission factors are provided by car type model, fuel and engine capacity as shown in Table 11. The vehicle stock was disaggregated by engine capacity using shares from the NTS.

with age greater than 16 years is considered. This follows Dargay and Hanly (2004a) who only consider individuals with legal age to drive in the UK. The estimation is carried out for $T=9$ years (from 1998 to 2006) and it distinguishes two regions ($H=2$), *Big cities* and the rest of Great Britain. The variable *Big cities* comprises London boroughs, met built-up areas and urban cities with a population of over 250 K. The rest of Great Britain is represented by cities with less than 250 K and rural areas. Three dummy variables to identify three periods are included in the models. *Period* 1 comprises years from 1998 to 2000, *Period* 2 from 2001 to 2003 and *Period* 3 from 2004 to 2006, this is done in order to reduce the number of parameters to be estimated.

The variables from the NTS used in the estimation are described in Table 1. The letters in brackets (i.e. $m1$, $m2$, $m3$, $m4$, and $m5$) denote the modules where the variables are used. Note that the sample size of the survey has been increasing across periods. This has been done to increase the representativeness of the survey.[15]

Table 1 shows strong car dependence as the mean of the variable *Transport mode* denotes that travelling by car is the main mode of transport. This pattern remains unchangeable across the analysed period. Moreover, the variable *cars in the household* have been increasing across the analysed period. This variable depends as I will show later on *Frequency of Buses*. In addition, according to a survey carried out by the DfT non-bus-users could be encouraged to use buses if punctuality and fares are improved.[16] Nevertheless, variables such as *Walk time to bus stop* and *Commute cost* which indicate improvements in these issues have not changed significantly across the three analysed periods.

Regarding vehicle level, the variables *Engine capacity* and *Vehicle size* show a tendency to buy more powerful and heavy vehicles which is contrary to any policy of mitigation as mentioned by Cuenot (2009). In addition, Table 1 shows that the mean of the variable *Usage* is around 7 which in the survey this number identifies the range 4300–5600 annual km. This implies that the daily distance driven in Great Britain (i.e. 12–15 km) has not changed significantly across the period analysed.

Regarding diesel cars, the variable *Fuel type* shows that these vehicles have seen a growing tendency across the analysed period despite of the fact of facing an annual average growth in diesel prices of 2%. Additionally unlike other European countries, in Great Britain diesel is more expensive than petrol. Nevertheless, what makes diesel cars competitive is the gap in fuel *Efficiency* between diesel cars and petrol ones. This gap was high at the beginning of the analysed period; however, it is currently getting narrower.

Although the dataset covers a considerable range of variables in the transport sector, there is a lack of information related to household income and prices of transport mode and cars. For this reason, the NTS dataset is complemented using public information provided by the Department for Transport (DfT) and the Automobile Association (AA). The variable *Commute cost* is built as follows. For the case of car price, the Automobile Association provides prices of driving per mile for diesel and petrol vehicles[17] and an average is estimated and used as cost of this modality. For bus and train prices, a cost is obtained from the NTS dataset where the total cost is divided by total distance travelled to get an estimation for the cost of travelling per mile. Finally, the cost of walking and cycling is set equal to zero.[18]

Improvements in public transportation to reduce the waiting time of commuters can be achieved by either making bus services more efficient or increasing the number of buses. Moreover, the effect of an increase in the number of buses in a region will be relative to each commuter's perception of *Bus frequency* which is reported in the NTS. Therefore, to analyse the effect of improvements in public transportation, I introduce the variable *Bus availability* which is estimated by multiplying *Bus frequency* and the number of buses in the region.[19]. This will allow me to evaluate the commuter's response of vehicle ownership to changes in the number of buses. However note that this model only estimates changes in energy consumption and CO_2 emissions coming from households' cars.

In discrete choice models it is common practice to normalise prices by an income variable.[20] Therefore the higher the individual's income, the smaller weight that those prices receive for those individuals. However, as previously mentioned, to introduce the effect of income in the estimations is complicated given that there is a lack of consistency across the years in the survey in this variable. Hence the variable *socioeconomic level* is used as proxy in the econometric specifications. The nature of this variable (bounded between 0 and 5) makes it to work better in some estimations than in others. Note, however, that other variables such as *Cars in the household*, distance travelled, *number of owned cars* and fuel consumed can be indicators of the household's income level. The criterion to choose among these variables in the econometric specification is based not only on statistical significance but also on accordance with economic theory. For instance, the variable *Car price* and *fuel price* are weighted by the variable *socioeconomic level* in the module for type and age vehicle choice while in the *usage* estimation *car price* is normalised by the amount of fuel consumed.

As previously mentioned, the structure of the model requires taking into consideration vehicle age given that this determines distance travelled, fuel consumption and CO_2 emissions. Hence to account for the fact that *Car price* changes according to the car's age, the price is adjusted using the estimation of price variation carried out by the Royal Automobile Club Foundation for Motoring.[21] Moreover, *Fuel price* is divided by the vehicle *Efficiency* to take into consideration that drivers face relative prices according to the vintage and efficiency of their vehicles that change across time. These variables are provided by the DfT in *Transport Statistics Great Britain* 2008[22].

To control for the fact that the degree of urbanisation plays an important role in designing transport policies, I follow Frondel and Vance (2010) who introduced the variable *Big cities*. In my estimation the variable *Big cities* comprises London boroughs, met built-up areas and urban cities with a population of over 250 K. The rest of Great Britain is represented by cities with less than 250 K and rural areas. The next table shows some of the key variables broken down by these two regions. The columns entitled *Period* show the absolute frequency whereas the columns beside show the relative frequency.[23]

Table 2 shows some important differences across regions. One can see that travelling by car is more popular in *other cities* than in *Big cities*. Consequently the use of public transportation is

[15] The manual that accompanies the dataset specifies that there are no major changes of the survey methodology across years apart from omission of some variables. Therefore pooling the data from these years is possible.

[16] Public experiences and attitudes towards bus travel 2009.

[17] See Moring Cost provided by the Automobile Association available at http://www.theaa.com/motoring_advice/running_costs/archive.html.

[18] See Hole and FitzRoy (2004).

[19] Available at http://www.dft.gov.uk/pgr/statistics/datatablespublications/vehicles/

[20] See Ben-Akiva and Lerman (1985). They include simultaneously in the econometric specification, prices normalised by income and an income variable. Therefore they are able to analyse jointly individual responses to relative prices and income effects.

[21] See Transport Price Indices, 2009, http://www.racfoundation.org/.

[22] This version is available at http://www.dft.gov.uk/pgr/statistics/datatablespublications/tsgb/.

[23] Absolute frequencies normalised by the total number of events.

Table 1
Variable definition and descriptive statistics.

Variable definition	**Source**	**Range of values**	**Period 1**			**Period 2**			**Period 3**		
			Mean	Std. dev	Sample	Mean	**Std. dev.**	**Sample**	**Mean**	**Std. dev.**	**Sample**
Number of tranfers (m1)	NTS	0=1 stage,1,=2 stages, …, 6=6 stages	0.1	0.3	60,907	0.1	0.3	113,361	0.1	0.3	147,054
Purpose of travelling (m1)	NTS	0=work, 1=in course of work, 2=education, 3=shopping, 4=holiday	1.5	2.5	60,907	1.4	2.6	113,361	1.5	2.6	147,054
Transport mode (m1)	NTS	1=walking or cycling, 2=car, 3= motorcycle, 4=bus, 5=train	2.2	0.9	60,907	2.2	0.9	113,361	2.2	0.9	147,054
Commuter age (m1)	NTS	0=16–19, 1=20–29,2=30–39,3=40–49 4=50–59, 5=60–69	2.8	1.5	60,907	2.9	1.5	113,361	2.9	1.5	147,054
Commute cost(m1)[a]											
(Pence per km)	Other	Car	22.1			23.3			23.2		
	Other	Motorcycle	16.1			17.1			17.0		
	NTS	Bus	12.7			13.7			15.9		
	NTS	Train	12.2			12.3			11.9		
Number of owned cars (m4)	NTS	0=none, 1=1,2=2,3=3,4=4	1.0	0.8	7965	1.1	0.8	16,349	1.1	0.9	21,175
Number of owned bicycles (m1)	NTS	0=none, 1=one, 2=two or more	0.7	0.8	7965	0.7	0.8	16,349	0.8	0.8	21,175
Members with full licence(m4)	NTS	0=none,1=1, …, 4=4	1.3	0.9	7965	1.3	0.9	16,349	1.3	0.9	21,175
Frequency of buses(m2)	NTS	0=less than once a day, 1=once a day, …, 2=1 an hour, 3=1 every half hour, 4=1 every quarter hour	3.0	1.0	7965	3.0	1.0	16,349	3.0	1.0	21,175
Household size(m2)	NTS	0=1 member, 1=2 members, …, 4=five	2.2								
Socioeconomic level (m1–m3, m5)	NTS	Five levels where 0 is the highest	1.5	1.3	7965	1.5	1.4	16,349	1.5	1.3	21,175
Employment (m3,m5)	NTS	1=full time employment, 0 otherwise	0.2	0.5	7965	0.2	0.5	16,349	0.2	0.5	21,175
Walk time to bus stop(m2)	NTS	0=6 min, 1=7–13 min, 2=14–26 min 3=27–43 min, 4=44 min or more	0.2	0.5	7965	0.2	0.5	16,349	0.2	0.5	21,175
Big cities(all)[b]	NTS	1=big cities, 0 otherwise	0.4	0.5	7965	0.4	0.5	16,349	0.5	0.5	21,175
Driver gender(m3)	NTS	1 if the driver is male, 0 otherwise	0.6	0.5	8371	0.6	0.5	18,143	0.6	0.5	24,552
Property(m3)	NTS	1 if the car is provided by a company	0.1	0.3	8371	0.1	0.2	18,143	0.0	0.2	24,552
Engine capacity(m3)	NTS	0=up to1500 and 1=more than 1500 cc	0.6	0.5	8371	0.6	0.5	18,143	0.6	0.5	24,532
Car size(m3)	NTS	0=small,1=medium, 2=large cars	1.4	1.3	8371	1.7	1.5	18,143	1.8	1.5	24,552
Fuel type (m3–m5)	NTS	0=petrol, 1=diesel	0.1	0.3	8371	0.2	0.4	18,143	0.2	0.4	24,552
Vehicle age(m3–m5)	NTS	0=up to 1 year, 1=1–2, 2=2–3, 3=3–5, 4=over 5 years	3.1	1.3	8371	3.0	1.4	18,143	3.1	1.3	24,552
Vehicle availability(m3)	NTS	0=regular use, 1=possibly will be used 2=new acquired vehicle	0.0	0.2	8371	0.0	0.2	18,143	0.0	0.2	24,552
Usage (m5)	NTS	Minimum value 0=312 and maximum 12=18,750 annual km	7.2	2.7		6.9	2.7		6.9	2.6	
Car price(m3–m5)[c]	Other	Petrol (Pence/km)	15.1			18.4			20.7		
		Diesel (Pence/km)	19.8			23.4			26.5		
Fuel price(m3–m5)[d]	DfT	Petrol (Pence/l)	7.2			7.6			8.6		
	DfT	Diesel (Pence/l)	7.4			7.8			8.9		
Efficiency(m3–m5)[e]	DfT	Petrol (km/l)	12.2			12.7			13.2		
	DfT	Diesel (km/l)	15.0			16.0			15.9		
Density(m4)[f]	Other	km/per capita	0.7			0.7			0.7		
Number of household(simulation)s	DfT	Millions	20,066			20,715			21,215		

[a] Car and motorcycle prices are an average estimated using information from the AA while the price of public transportation are estimated dividing total journey distance and cost from the NTS.
[b] The variable *Big cities* includes London boroughs, met built-up areas and urban cities with a population of over 250 k.
[c] Estimated average price that includes cost of depreciation, service, insurance cost and tax road and other costs. However, it does not include fuel cost.
[d] Average for the period estimated using the price of unleaded petrol and ultra low sulphur diesel.
[e] Average efficiency of new cars.
[f] It is estimated by dividing the total road length (DfT) by population per region.

considerably inferior in *other cities* than in *big cities*. Additionally, diesel share has been growing across years and it is higher in *other cities*. The proportion of old vehicles is almost the same across these two regions. These regional differences show that potentially the same policy can have different outcomes in these two regions.

It is important to identify the characteristics of the buyers of diesel cars because it is an indicator of the intensity of the use of these vehicles. In this sense Table 3 shows that there are more male drivers who own a diesel car than female ones. Notice also that for every period there are heavier diesel vehicles in the vehicle stock. In both regions *property* (i.e. 1 if a company pays for the vehicle cost, 0 otherwise) is higher for diesel vehicles than for the petrol ones. The same occurs also for the variable *employment* (i.e. 1 if the household's main earner has a full time job, 0 otherwise). Additionally, compared with petrol cars owners, there are fewer households with high socioeconomic level that own diesel cars. This shows that income levels are important drivers for the diesel vehicle penetration as pointed out by Bonilla (2009). Regarding *Vehicle size* and *Vehicle capacity*, it can be seen as pointed out by Schipper and Fulton (2009) that diesel cars tend to be bigger vehicles that need more power to compensate for this disadvantage. Moreover, as the authors noted

Table 2
Big cities and rest of Great Britain.

Variable	*Other cities*			*Big cities*		
	Period 1 (%)	**Period 2 (%)**	**Period 3 (%)**	**Period 1 (%)**	**Period 2 (%)**	**Period 3 (%)**
Number of trips						
Walking and cycling	10	10	10	10	10	10
Car	82	83	83	70	70	69
Motorcycle	1	1	1	1	1	1
Bus	5	4	4	12	12	12
Rail	2	2	2	7	8	8
Diesel share	15	19	24	11	15	18
Vehicles over 5 years	60	56	56	59	55	56

Table 3
Characteristics of the car and owners by type of fuel.

Item	Fuel	Category	Period 1 (%)	Period 2 (%)	Period 3 (%)
Driver Gender	Petrol	Male	59	57	55
	Diesel	Male	71	74	73
Property	Petrol	Company	7	5	3
	Diesel	Company	12	12	12
Employment	Petrol	Full time	70	67	67
	Diesel	Full time	79	78	77
Socioeconomic level	Petrol	High	63	64	65
	Diesel	High	55	56	61
Car size	Petrol	Big vehicles	12	17	18
	Diesel	Big vehicles	32	46	50
Vehicle capacity	Petrol	Over 1500 cc	53	53	53
	Diesel	Over 1500 cc	93	96	92
Vehicle age	Petrol	Over 5 years	62	57	59
	Diesel	Over 5 years	46	53	46
Vehicle usage	Petrol	Over 9 daily km	77	73	73
	Diesel	Over 9 daily km	88	88	89

diesel cars are used more intensively than their counterparts as the variable *Vehicle usage* shows.

3.2. Econometrics results

In the next sections, the results from the model will be presented. The modules of estimation are as follows: (1) module of transport, (2) ownership, (3) vehicle type, and (4) usage. In addition, in the next section the results of the policy simulation will be analysed.

3.2.1. Module of transport mode

The estimates for the *CML* and the *NML* are shown in Table 4.

Notice that the estimation assumes that the *Commute cost* is relative to the distance that commuters travel, this follows Ben-Akiva and Lerman (1985). This estimate shows that the election of the transport mode is highly sensitive to prices which allow designing policies to reduce car dependence favouring public transport modes such as train and buses. The CML and NML models show similar effects of the explanatory variables on the dependant one. However, the *CML* is chosen for the policy experiment in the following section as the dissimilarity parameters in the *NML* are out of the theoretical range.

When people face several stages in their journey, travelling by bus and train are more preferable than other alternatives, as it can be seen in Table 4 where estimates across choices for *number of stages* are statistically significant and positive as by Train (1980).[24]

Table 4
CML and *NML* as specified in expressions (2) and (3).
Dependent variable: transport mode codified from 1 to 5.

	CML	*CML*	*NML*	*NML*
Alternative specific				
Independent variables				
log(*commute cost*/distance)	−1.107***	(0.007)	−1.107***	(0.007)
Case specific				
Independent variables				
Big cities = 1				
2	−0.227***	(0.015)	−0.225***	(0.015)
3	0.028	(0.047)	−0.150***	(0.022)
4	0.873***	(0.021)	0.738***	(0.026)
5	1.496***	(0.031)	1.849***	(0.057)
Number of Transfers				
2	−0.682***	(0.085)	−0.692***	(0.086)
3	−1.840***	(0.289)	−0.999***	(0.121)
4	1.699***	(0.085)	0.766***	(0.134)
5	3.386***	(0.087)	4.602***	(0.199)
Purpose of travelling				
2	−0.056***	(0.003)	−0.056***	(0.003)
3	−0.488***	(0.040)	−0.180***	(0.021)
4	−0.050***	(0.004)	−0.024***	(0.005)
5	−0.164***	(0.009)	−0.268***	(0.018)
Commuter age				
2	0.198***	(0.005)	0.196***	(0.005)
3	0.008	(0.018)	0.137***	(0.009)
4	0.049***	(0.007)	0.191***	(0.028)
5	−0.177***	(0.009)	−0.620***	(0.083)
Socioeconomic level				
2	−0.141***	(0.006)	−0.140***	(0.006)
3	−0.002	(0.015)	−0.102***	(0.009)
4	0.125***	(0.008)	0.247***	(0.017)
5	−0.280***	(0.014)	−0.681***	(0.047)
Number of owed bicycles				
2	−0.053***	(0.009)	−0.052***	(0.009)
3	0.152***	(0.027)	0.008	(0.014)
4	−0.538***	(0.012)	−0.596***	(0.019)
5	−0.498***	(0.017)	−0.347***	(0.041)
Year specific effects				
Period 1				
Period 2				
Period 3				
Dissimilarity parameters				
$\tau_{non\ motorised}$			1	
$\tau_{private\ motorised}$			0.286***	(0.039)
$\tau_{public\ motorised}$			2.582**	(0.240)

Note that 2 denotes travelling by car, 3 motorcycle, 4 bus and 5 train. Walking and cycling is the base choice alternative. Standard errors are given in parenthesis. Year effect parameters are available upon request from the author.
*Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

[24] The number of stages travelling by car and motorcycle shows that some commuters do not complete their total journey using these modes. Therefore they also use other methods of transportation.

The variable *Big cities* is statistically significant and shows that living in big cities reduces the probability of travelling by car and increases the probability of travelling by public transportation. Notice that the variable *Socioeconomic level* shows that the decision about mode of transport is strongly related to income levels .Commuters with low income will rarely travel either by car or train. Regarding the number of bicycles attributed to the commuter's household, it affects negatively the probability of travelling by car, bus, or train. However, it increases the probability of travelling by motorcycle and therefore this mode and cycling are complements rather than substitutes. Further research is needed, as in this estimation, encouraging the use of bicycle could also increase the use of motorcycle having perverse effects in terms of emissions.

The intercept in the *CML* model is the average effect of the unincluded factors in the utility of the different modalities of transport related to the base line category (see e.g. Train, 2003). Therefore, its sign can be either positive or negative. The intercept in Table 4 is broken down per different years. This is represented by the estimates of the *Year specific effects*. These are not shown in Table 4. However, they are negative and statistically significant. Additionally their values are very similar across the analysed period.

3.2.2. Ownership module

The parameters for the first stage related to household's decision to own a car can be seen in Table 5.

Table 5 shows the estimation of the car ownership regression. Here, I use two different econometrics models that use two different accumulative distribution functions for the residuals. One can see that up to a scalar the parameters show a similar relationship between car ownership and the explanatory variables. Notice that the estimate for *Bus availability*[25] has a negative effect on the decision to buy a car. In the same vein, *walk time to bus* station increases the probability of buying a car. This shows that improving public transportation can encourage travellers to reduce car dependence. Therefore, this can reduce the amount of energy used and emissions in the sector.

As in Chiou et al. (2009), the estimates related to *density* show a positive effect on the probability of car ownership. Additionally as shown in Table 5, for B*ig cities* increases of the length of road per capita has a smaller effect than in *other cities*.

Regarding the effect of the *socioeconomic level,* it is found that high socioeconomic levels have a positive effect on car ownership as in Train (1980). Moreover, time dummies are statistically significant showing that the utility of car ownership is affected by unknown factors differently across time.

3.2.3. Module of vehicle type

The estimates for the *CML* and the *NML* are shown in Table 6.

Notice that prices are weighted by *socioeconomic* level to make them relative to each individual's income level.[26] Also note that in both specifications (i.e. *CML* and *NLM*) the estimates related to the ratio *fuel price/efficiency* have a stronger effect on the decision of the kind of vehicle than the estimates for the ratio *car price*. This fact has important policy implications as changes in the price of diesel will be more effective for increasing the number of diesel vehicles than changes in price of diesel cars. However, environmental implications have to be taken into account and this is one of the policy exercises that will be analysed in the next section.

In both econometric specifications *car size* and being a male driver increase the probability of buying a diesel vehicle. The

[25] This variable is constructed by multiplying the information about bus frequency provided by the NTS and the number of buses provided by the Department for Transport.

[26] Note that the variable *Socioeconomic level* is bounded between 0 and 5 and therefore prices were multiplied the factor (1+*Socioeconomic level*).

Table 5
Dependent variable: 1 if the household is a vehicle owner, 0 otherwise.

	Logit		Probit	
Log(bus availability)	−0.359***	(0.028)	−0.212***	(0.016)
Household size	0.998***	(0.018)	0.538***	(0.009)
Walk time to bus	0.101***	(0.024)	0.061***	(0.014)
Socioeconomic level	−0.432***	(0.009)	−0.255***	(0.005)
Density big cities	0.555***	(0.067)	0.323***	(0.039)
Density other cities	1.026***	(0.060)	0.604***	(0.035)
Period 1	0.449***	(0.136)	0.364***	(0.077)
Period 2	0.591***	(0.136)	0.446***	(0.077)
Period 3	0.675***	(0.136)	0.495***	(0.077)

*** Significant at 1% level.

Table 6
Dependent variable is codified as numbers from 1 to 8 for different combination of fuel type and age.

	CML	*CML*	*NML*	*NML*
Alternative specific				
Independent variable				
*(Car price)*socioeconomic*	−0.012***	(0.001)	−0.001	(0.000)
(Fuel price/efficiency) Socioeconomic*	−0.065***	(0.008)	−0.001	(0.000)
Case specific				
Independent variable				
Driver gender(male=1)				
2	−0.007	(0.047)	−0.000	(0.001)
3	−0.025	(0.047)	−0.000	(0.001)
4	0.228***	(0.042)	0.003***	(0.000)
5	0.309***	(0.081)	0.262***	(0.000)
6	0.374***	(0.065)	0.263	(0.213)
7	0.272***	(0.069)	0.262	(0.215)
8	0.439***	(0.053)	0.264	(0.212)
Property(1=if company)				
2	−0.360***	(0.068)	−0.004	(0.003)
3	−1.381***	(0.084)	−0.0164	(0.014)
4	−2.813***	(0.086)	−0.033***	(0.000)
5	0.667***	(0.089)	0.728***	(0.000)
6	0.240***	(0.079)	0.711***	(0.101)
7	−1.089***	(0.111)	0.695***	(0.089)
8	−2.225***	(0.113)	0.695***	(0.089)
Employment(1=full time)				
2	0.042	(0.049)	0.001	(0.000)
3	0.161***	(0.050)	0.002	(0.002)
4	0.005	(0.044)	0.000***	(0.000)
5	0.356***	(0.091)	0.251***	(0.000)
6	0.285***	(0.071)	0.251	(0.285)
7	0.348***	(0.075)	0.251	(0.286)
8	0.271***	(0.055)	0.251	(0.286)
Household size				
2	−0.005	(0.021)	0.000	(0.000)
3	0.049**	(0.021)	0.001	(0.001)
4	0.072***	(0.019)	0.001***	(0.000)
5	0.135***	(0.033)	0.053***	(0.000)
6	0.101***	(0.027)	0.053***	(0.000)
7	0.124***	(0.029)	0.053	(0.059)
8	0.080***	(0.023)	0.053	(0.059)
Car size				
2	−0.065***	(0.017)	−0.001	(0.001)
3	−0.090***	(0.017)	−0.001	(0.001)
4	−0.106***	(0.015)	−0.001***	(0.000)
5	0.324***	(0.024)	0.319***	(0.000)
6	0.264***	(0.021)	0.318***	(0.000)
7	0.264***	(0.022)	0.317***	(0.013)
8	0.182***	(0.018)	0.317***	(0.013)
Engine capacity				
2	0.059	(0.052)	0.001	(0.001)
3	0.136***	(0.052)	0.002	(0.001)
4	0.049	(0.046)	0.001***	(0.000)
5	1.8399***	(0.115)	2.029***	(0.000)
6	1.9083***	(0.084)	2.031***	(0.000)

Table 6 (*continued*)

	CML	CML	NML	NML
7	2.2564***	(0.088)	2.038***	(0.109)
8	2.1949***	(0.070)	2.036***	(0.108)
Big cities = 1				
2	−0.008	(0.044)	−0.000	(0.001)
3	−0.006	(0.045)	−0.000	(0.001)
4	−0.038	(0.040)	−0.001***	(0.000)
5	−0.139**	(0.072)	−0.293***	(0.000)
6	−0.272***	(0.060)	−0.294	(0.178)
7	−0.295***	(0.065)	−0.294	(0.177)
8	−0.386***	(0.050)	−0.296	(0.178)
Year specific effects				
Period 1				
Period 2				
Period 3				
Dissimilarity parameters				
τ_{petrol}			0.012	(0.010)
τ_{diesel}			0.013	(0.011)

Moreover, 2 denotes petrol vehicles from 1 to 3 years, 3: from 3 to 5 and 4: over 5. The numbers from 5 to 8 refer to the same car type models for diesel vehicles. The alternative base is 1 which denotes petrol vehicles up to 1 year. Year effect parameters are available upon request from the author.

* Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

preference of male drivers for heavy vehicles is consistent with Chiou et al.'s (2009) results. Therefore making these vehicles lighter could attract female drivers. Additionally, making lighter cars will decrease levels of CO_2 emissions as pointed out by Cuenot (2009). Moreover, the model shows that not only making lighter vehicles is important to increase vehicle diesel penetration but also making cheaper ones. That is, it is more likely that drivers prefer a diesel vehicle either when the company pays for the vehicle cost or when the driver has a full time job. This is shown in the estimates for the binary variables *Property* and *Employment* where the former takes value of 1 if a company pays for the vehicle cost and 0 otherwise while in the latter one 1 is assumed for full time job 0 otherwise. Therefore income is an important driver for diesel vehicle penetration as pointed out by Bonilla (2009). The fact that the purchaser characteristics are identified can help to design more efficient policies. For instance imposing a tax on the purchase of heavy vehicles and taxing company cars according to the usage or CO_2 emissions can have more immediate results.

Regarding regional effects, the model shows that living in *Big cities* decreases the probability of buying a diesel car. This is due to the fact that in *Big cities* there are more transportation choices and therefore spending more money on expensive vehicles is needless.[27] *The year specific effects* are not shown in Table 6, but they are only statistically significant for diesel vehicles. Moreover they are negative and decreasing across the analysed period. As in the transport module they represent the relative average effect of the unincluded factors in the utility of the diesel vehicles.

According to Train (2003) only the *MNL* could capture substitution patterns more realistically. However, the dissimilarity parameters denoted as τ_{petrol} and τ_{diesel} are statistically not significant and therefore they cannot explain the analysed dataset. Hence, in the policy experiment the *CLM* specification is used for this module.[28]

3.2.4. *Vehicle availability*

Changes in the vehicle stock are measured by changes in the probability of having a new acquired vehicle. The estimates from the ordered probit model are shown in Table 7.

Both models show that the probability of choosing a new acquired vehicle is more sensitive to changes in the ratio *fuel/efficiency* than to changes in the variable *car price*. Moreover, this probability also increases for male drivers; and with the number of cars owned by the households this provides some information about household's income level. As mentioned in Section 2.4 the probit model is used in the policy simulation section.

3.2.5. *Usage*

Regarding the estimates for the intensity in car usage, I used a lineal specification following Chiou et al. (2009), who show that the intensity of driving is more sensitive to changes in the ratio *fuel/efficiency* than to changes in the ratio *car price/fuel consumed*. The same result is obtained and shown in Table 8.

Moreover, Table 8 shows the following results that are in line with the ones obtained by Chiou et al. (2009): (1) vehicle age has a negative effect in the vehicle usage, (2) being a female driver reduces the amount of usage, and finally (3) drivers with higher income use cars more intensively than drivers with low income. Therefore vehicle age reduces the intensity of car usage, women tend to undertake shorter journeys than men do and high income drivers use car more intensively than lower income ones. Year effects are not shown in this table; however, they are all positive and statistically significant. They represent, as in discrete choice models, the average effect of unknown factors across years (see for example Train, 2003). However note that estimates are not relative to any base-line category in lineal models since they are not a Random Utility Models (RUM).

3.2.6. *Summary of the three different specifications*

Table 9 shows some of the key results obtained from the econometric specifications.

4. Policy analysis

The econometric results from the previous section are shown in Table 9. It shows that improvements in public transportation and changes in fuel prices are relevant polices to be analysed. Therefore effects on improvements of public transportation are estimated by the two first scenarios.[29] Notice that increasing the number of buses is not the only way to reduce the commuter's waiting time. Increasing efficiency of public transportation can reach the same goal. However, in my estimation I analysed the effect of changes in the number of buses to induce commuters to reduce car dependence. In addition, I analysed the effect of taxes on petrol prices and a reduction in the diesel price. Notice that a reduction in the diesel price can be explained by a reduction in the tax to this diesel. Moreover, given that *fuel price* enters into the model as the ratio *fuel price/fuel efficiency*, a reduction in the price of diesel can also be seen as an increase in *fuel efficiency* in the econometric specification.

Table 10 shows the scenarios, the variables and modules involved in the policy simulation.

In the first column one can see the policies to be evaluated; in the second one the variables that are manipulated; and in the third one the modules of the model that are involved. The

[27] See Table 2 for the relative frequency of number of trips by modality.

[28] The models and the simulation results from the policy experiments are coded in Stata 10 as in Cameron and Trivedi (2009).

[29] Note that a reduction of fares and increases of the frequency of buses are mentioned in the survey *Public experiences and attitudes towards bus travel 2009* as factors that can encourage commuters to use public transportation.

percentages chosen are arbitrary; however, the model can be evaluated at any percentage of policy change.

In order to estimate CO_2 emissions, the following factors are taken from the DfT and are shown in Table 11.

The key variables estimated with the model econometric specification and the structure previously described are shown in Table 12.

The first scenario to be analysed is an improvement in public transportation. Tables 13 and 14 show the effect of an increase of 10% in the number of buses and 15% of subsidies in the bus price. The relative changes are with respect to the base scenario. Also note that *usage* in this section refers to vehicle-kilometres that is the product of the number of vehicles and the kilometres that each vehicle is used. Additionally the consumption of petrol and

Table 7
Dependent variable: (1) vehicle in regular use, (2) possibly will come into use and (3) new acquired vehicle.

	Oprobit		**Ologit**	
log(*fuelprice*/*efficiency*)	−0.826***	(0.240)	−1.334**	(0.607)
log(*car*/*distance*)	−0.103***	(0.031)	−0.297***	(0.080)
Driver gender(*male*=1)	0.224***	(0.025)	0.572***	(0.061)
Number of owned cars	0.178***	(0.014)	0.452***	(0.030)
Big cities=*1*	−0.000	(0.024)	0.007	(0.058)
Fuel type (*diesel*=1)	−0.372***	(0.051)	−0.835***	(0.126)
Period 1	0.076**	(0.036)	0.097	(0.085)
Period 2	0.120***	(0.027)	0.256***	(0.065)
η_{a1}	4.21***	(0.536)	7.498***	(1.372)
η_{a2}	4.71***	(0.533)	8.783***	(1.361)

** Significant at 5% level.
*** Significant at 1% level.

Table 8
Dependent variable ln(*Driven annual kilometres*).

log(*fuelprice*/*efficiency*)	−0.460***	(0.067)
log(*car price*/*fuel consumed*)	−0.305***	(0.008)
Ageofdieselcar	−0.193***	(0.005)
Age of petrol car	−0.102***	(0.004)
Driver gender(*male*=1)	0.15***	(0.007)
No Full licence	0.038***	(0.005)
Employment(1=*full time*)	0.272***	(0.008)
Household size	0.021***	(0.004)
Socioeconomic level	−0.188***	(0.006)
Region	−0.062***	(0.007)
Year		
R^2		0.992

*** Significant at 1% level.

Table 10
Model strategy of simulation.

Polices	*Variables to manipulate*	*Model manipulation*
Increasing buses (10%)	*Bus availability*	m2
Subsidising bus fees (15%)	*Commute cost*	m1
Increase in tax on petrol cars (5%)	*Average fuel price*, *fuel price*	m2, m3, m4
Reduction in diesel price (5%)	*Commute cost*, *fuel price*	m1, m3, m4

Table 11
Average CO_2 emission factors used in the estimation.[a]

Item	Fuel	*Category (year)*	*Period* 1	*Period* 2	*Period* 3
Emission factors (kg/km)	Petrol 1400 cc[b]	Up to 1	135.8506		
		From 1 to 3	146.5898		
		From 3 to 5	146.5898		
		Over 5	166.6889		
	Petrol 1400–2000 cc	Up to 1	213.6013		
		From 1 to 3	225.3541		
		From 3 to 5	225.3547		
		Over 5	254.4713		
	Diesel 1400 cc	Up to 1	98.8368		
		From 1 to 3	98.0836		
		From 3 to 5	98.0836		
		Over 5	115.5358		
	Diesel 1400–2000 cc	Up to 1	182.4086		
		From 1 to 3	195.2804		
		From 3 to 5	195.2804		
		Over 5	230.3365		

[a] Average factors of different vehicle ages estimated using data from DfT available from http://www.dft.gov.uk/pgr/roads/environment/emissions/.
[b] cc stands for cubic capacity.

Table 9
Main results and policy implications.

Module	**Variable**	**Main results**	**Policy implication**
Transport mode	*Commuting cost* and *Socioeconomic level*	Prices and income are important drivers in the mode choice	Reducing public transport fares can increase the use of it
	Big cities	Commuters from *Big cities* prefer travelling by public transportation.	Policies of improving public transportation will have a bigger impact in *Big cities*.
Ownership	*Bus availability* *Walk time to bus stop*	Increasing the number of buses can prevent households from buying a car. Additionally, reducing the walk time to bus stop decreases the probability of being a car owner	Improvements in public transportation have a positive effect on reducing the number of cars owned by households
Age and fuel	*Fuel price*/*efficiency*	Fuel price and efficiency have a bigger effect on the decision of the type and new purchases of vehicles	Mitigation policies have more significant effects if fuel prices are used as instrument instead of using car prices
	Property, employment, Gender, Vehicle size and *Engine capacity*	Diesel vehicles are preferred by men with full time employment and preferences for big vehicles. Moreover, if a car is a company car, the probabilities of being a diesel car increases. As noted by Schipper and Fulton (2009) these variables influence significantly the probability of choosing a diesel vehicle	The fact that the market of diesel cars is clearly identified by these factors shows that an efficient design of polices has to consider not only purchasers but also car manufacturers. In addition, the fact that companies and individuals with high income tend to buy diesel cars shows that potentially the use of these vehicles will be intense. Consequently these facts have to be considered when a policy is designed
	Big cities	Diesel cars are less likely to be purchased in big cities	This is explained by the fact that car dependence is stronger in other cities
Usage	*Fuel price, efficiency*	These variables have a stronger effect on the decision about the distance travelled than *car price*	Taxes on diesel price can reduce the distance travelled but increases in the vehicle efficiency will increase it

Table 12
Base scenario.

Concept	Units	*Other cities*			*Big cities*		
		Period 1	**Period 2**	**Period 3**	**Period 1**	**Period 2**	**Period 3**
Vehicles	Thousand vehicles						
Petrol		10	11	10	7	7	8
Diesel		2	3	3	1	1	2
Consumption	Thousands of tonnes of fuel						
Petrol		10	10	8	6	6	6
Diesel		2	2	3	1	1	1
CO_2 *emission*	ktonnes						
Petrol		29,566	28,135	25,303	17,747	16,471	17,263
Diesel		5260	7675	9620	2509	3472	4781

Table 13
Regional effect of increasing 10% in the number of buses.

	Other cities			***Big cities***		
	Period 1 (%)	*Period 2 (%)*	*Period 3 (%)*	*Period 1 (%)*	*Period 2 (%)*	*Period 3 (%)*
Change in diesel vehicles	−0.7	−0.6	−0.6	−0.9	−0.9	−0.8
Change in petrol vehicles	−0.7	−0.6	−0.6	−0.9	−0.9	−0.8
Total changes in energy consumption	−0.7	−0.6	−0.6	−0.9	−0.9	−0.8
Total changes in CO_2 emissions	−0.7	−0.6	−0.6	−0.9	−0.9	−0.8
Diesel usage	−0.7	−0.6	−0.6	−0.9	−0.9	−0.8
Petrol usage	−0.7	−0.6	−0.6	−0.9	−0.9	−0.8

Table 14
Regional effects of a subsidy of 15% in bus fares.

	Other cities			***Big cities***		
	Period 1 (%)	*Period 2 (%)*	*Period 3 (%)*	*Period 1 (%)*	*Period 2 (%)*	*Period 3 (%)*
Change in diesel vehicles	0.0	0.0	0.0	0.0	0.0	0.0
Change in petrol vehicles	0.0	0.0	0.0	0.0	0.0	0.0
Total changes in energy consumption	−0.8	−0.8	−0.8	−2.2	−2.1	−2.1
Total changes in CO_2 emissions	−0.8	−0.8	−0.8	−2.2	−2.1	−2.1
Diesel usage	−0.8	−0.8	−0.8	−2.2	−2.1	−2.1
Petrol usage	−0.8	−0.8	−0.8	−2.2	−2.1	−2.1

diesel has been converted into energy to estimate the *Total changes in Energy Consumption*.

One can see in Table 13 that increasing the number of buses reduces all the levels of the variables given that it reduces the number of vehicles in the stock while in Table 14 a subsidy in bus price reduces only the usage of vehicles and therefore energy consumption and emissions.

Both policies show significant differences across regions. Improving public transportation has a bigger impact in *Big cities*. This is not surprising given that in *Big cities* the demand for public transportation is higher. In addition, Table 14 shows that subsidising bus fares has a stronger effect than increasing the number of buses. Notice that in this experiment the price of travelling by bus is reduced for *all* commuters, however, to set an effective scheme of subsidies it is necessary to consider age, socioeconomic level, employment, disabilities, etc. Notice also that the changes are the same for all the concepts in both tables given that changes in either number of buses or bus fares affect only two modules of the model and therefore these changes are transmitted in the whole system proportionally. It is important to notice that the model is taking into account the amount of energy and emissions coming *only* from household and consequently emissions coming from buses or an*other* method of transportation *are not considered* in my estimation.

Regarding a reduction in diesel price/increase of efficiency, Table 15 shows that under this scenario energy consumption and consequently the amount of CO_2 emissions increase.

This scenario shows a considerable increase in the vehicle *usage* given that this policy prompts a *rebound effect*. This effect is coming from two sources: petrol car owners switching to diesel cars and an increase of the use intensity of the owners that already have a diesel car. Consequently this policy increases energy consumption and CO_2 emissions. Therefore unlike Al-Hinti et al. (2007), Jeong et al. (2009), and Zervas (2006), and according to Frondel et al. (2007) and Schipper et al. (2002) having more efficient vehicles increases CO_2 emissions and therefore as in Bonilla (2009), policies focused unilaterally on increasing diesel penetration will not solve the problem of high energy consumption and emissions levels.

Notice that a decrease of 5% in diesel price prompt an average increase in *Diesel usage* of 6% and 7% across the analysed period in *other cities* and *Big cities*. This implies an estimated Own Price Elasticity (*OPE*) of 1.2 and 1.4. Therefore as noted by Schipper et al. (2002) the *rebound effect elasticity* in Europe is greater than 0.5.

Additionally according to the authors the elasticity is bigger where there are more options of public transportation. Consequently in *Big cities* the *rebound effect* is larger than in *other cities*.

Table 15
Regional effect of decreasing 5% of diesel prices.

	Other cities			*Big cities*		
	Period 1 (%)	*Period 2 (%)*	*Period 3 (%)*	*Period 1 (%)*	*Period 2 (%)*	*Period 3 (%)*
Change in diesel vehicles	4.5	4.3	3.5	4.7	4.5	3.8
Change in petrol vehicles	−0.8	−1.0	−1.1	−0.6	−0.8	−0.8
Total changes in energy consumption	0.4	0.6	0.7	0.3	0.6	0.8
Total changes in CO_2 emissions	0.4	0.7	0.7	0.3	0.6	0.8
Diesel usage	6.7	6.8	5.5	6.9	7.3	6.9
Petrol usage	−0.8	−1.0	−1.1	−0.6	−0.8	−0.8

Table 16
Regional effect of a tax of 5% in petrol price.

	Other cities			*Big cities*		
	Period 1 (%)	*Period 2 (%)*	*Period 3 (%)*	*Period 1 (%)*	*Period 2 (%)*	*Period 3 (%)*
Change in diesel vehicles	4.6	4.9	4.1	4.9	5.2	4.5
Change in petrol vehicles	−0.9	−1.3	−1.4	−0.7	−1.0	−1.1
Total changes in energy consumption	−2.1	−1.7	−1.3	−1.8	−2.1	−1.9
Total changes in CO_2 emissions	−2.1	−1.6	−1.2	−1.8	−2.0	−1.8
Diesel usage	4.6	4.9	4.1	4.9	5.2	4.5
Petrol usage	−3.3	−3.4	−3.3	−2.8	−3.5	−3.5

Notice also that the same elasticities measure the response of fuel consumption to changes in energy prices.[30] Therefore a 5% decrease in diesel price will prompt a reduction in the demand for petrol of 1% and 0.7% in *other cities* and *Big cities* respectively. This implies an estimated Cross Price Elasticity (*CPE*) of 0.2 and 0.1, respectively. It is difficult to find estimates for CPE of diesel and petrol in the literature. One study was carried out by Chandrasiri (2006) who estimated *CPE* for Sri Lanka using a partial approach applied to aggregate data. He found an estimate of 0.1.

Regarding *Change in Diesel vehicles* it can be seen that across regions on average there is a change of 4% in this variable for a change of 5% in diesel price. This represents an estimated OPE for vehicles of 0.8. Kim et al. (2006) used a partial approach based on a stated preferences method for the Korean economy. They found an estimated OPE of 0.6. Additionally they found an estimated CPE for diesel and petrol vehicles of 0.4 while I found that a decrease of 5% in diesel prices prompts a reduction of 1% on *Change in Petrol vehicles*. This implies an estimated CPE of 0.2. The differences between my estimates and the ones given in the literature can be attributed to methodological and market differences. For instance based on the data reported by Kim et al. (2006), in Korea unlike Great Britain diesel is cheaper than petrol.

Taxes on petrol prices are the next scenario to be analysed. Table 16 shows that a tax on petrol vehicles increases the number of diesel vehicles, however, it does not encourage drivers to increase the intensity of using these vehicles.

Note that *Diesel usage* is exactly the same as *Change in Diesel vehicles* and therefore diesel drivers are not induced to drive more. However, there are still some problems to be solved. As previously mentioned, the reduction in CO_2 emissions is not the end of the problem given that diesel cars have a higher emission of particulates. The use of filters in these cars can reduce this problem, however, the purchases of diesel cars are associated with purchases of large and heavy vehicles and consequently this policy is also increasing the average weight of the vehicle stock. Therefore the advantages of having more efficient vehicles can be offset by the increase in their average weight.

This scenario is also useful given that it allows me to estimate an OPE for petrol consumption. I found that an increase of 5% in petrol price results in an average reduction in *Petrol usage* of 3% in both regions. In addition, as previously mentioned these changes are the same for fuel consumption. Therefore this implies an *OPE* of 0.65 which is in line with the average provided by Graham and Glaister (2002). The authors provide a survey of own price elasticities for cross section studies and they report a long run elasticity for cross section studies of 0.84.[31]

Policies that are applied in an isolated way tend to omit the effect of other variables and therefore a combination of policies can give a more efficient result. In this sense Table 17 shows the effect of a combination of polices. As is shown at the beginning of this analysis, increasing the use of public transportation via more buses and cheaper fares reduces energy consumption and emissions. The emissions and economic problems associated with this scenario can be solved by making public transportation more efficient rather than increasing the number of buses. Additionally, choosing the right scheme of bus subsidies can reduce its economic burden.

This scenario shows the potential of improvements in public transportation to reduce *Rebound effects*. The combination of either of these polices with a tax on petrol prices can allow improvements in the average fuel efficiency and at the same time reducing the *rebound effect*. This is shown in Table 18 when combining the increase of number of buses with a tax in petrol price reduces energy consumption and the amount of emissions.

This policy reduces the number of vehicles and therefore has a higher effect on energy consumption and CO_2 emissions than the previous simulations. Consequently including improvements in public transportation in the design of mitigation polices is a more effective mitigation tools. Note that an increase in the number of buses and fare subsidies along with petrol taxes can have even a higher reduction in energy consumption and CO_2 emissions than

[30] This is due to the fact that fuel efficiencies from the base scenario and the comparison one are the same. Note that fuel consumption is estimated using *Usage* and efficiencies as depicted in the methodological section.

[31] The authors defined long run as period of more than 1 year.

Table 17
Regional effect of an increase of 10% in the number of buses and 15% of a subsidy in bus fares.

	Other cities			*Big cities*		
	Period 1 (%)	*Period 2 (%)*	*Period 3 (%)*	*Period 1 (%)*	*Period 2 (%)*	*Period 3 (%)*
Change in diesel vehicles	−0.7	−0.6	−0.6	−0.9	−0.9	−0.8
Change in petrol vehicles	−0.7	−0.6	−0.6	−0.9	−0.9	−0.8
Total changes in energy consumption	−1.5	−1.4	−1.4	−3.1	−3.0	−2.9
Total changes in CO_2 emissions	−1.5	−1.4	−1.4	−3.1	−3.0	−2.9
Diesel usage	−1.5	−1.4	−1.4	−3.1	−3.0	−2.9
Petrol usage	−1.5	−1.4	−1.4	−3.1	−3.0	−2.9

Table 18
Regional effect of an increase of 10% in the number of buses and a 5% tax on petrol price.

	Other cities			*Big cities*		
	Period 1 (%)	*Period 2 (%)*	*Period 3 (%)*	*Period 1 (%)*	*Period 2 (%)*	*Period 3 (%)*
Change in diesel vehicles	4.0	4.2	3.5	4.0	4.3	3.6
Change in petrol vehicles	−1.5	−1.9	−2.0	−1.6	−1.9	−1.9
Total changes in energy consumption	−2.7	−2.3	−1.9	−2.7	−2.9	−2.7
Total changes in CO_2 emissions	−2.7	−2.2	−1.8	−2.7	−2.9	−2.6
Diesel usage	4.0	4.2	3.5	4.0	4.3	3.6
Petrol usage	−3.9	−4.0	−3.9	−3.6	−4.3	−4.3

the ones shown in Table 18. However, these polices have to be reinforced to control possible *rebound effects* by the following polices: (1) Keeping higher diesel prices than petrol ones as followed in Great Britain can reduce *rebound effects* as this discourages diesel drivers to increase the usage intensity, and (2) making mandatory the use of filters for diesel vehicles can also reduce the impact of the emission of particulates. Additionally, it is necessary to implement polices to prevent purchasers from buying big vehicles as this is another source of the *rebound effect*. A possible mechanism can be similar to the *French bonus*[32] which according to Cuenot (2009) can reduce the amount of heavy vehicles and therefore the amount of CO_2 emissions. It is important to notice that alternative policies addressed to reduce car usage needs to consider characteristics such as *property*, *socio-economic level* and *vehicle size* as they proved in the mode to be important in the choice of vehicle and intensity of using these vehicles.

5. Conclusions

In this paper, an integral approach was used to analyse the effect of policies of increasing diesel vehicle penetration on energy consumption and CO_2 emissions. Using a survey carried out in Great Britain, it was found that diesel vehicle penetration faces technical limitations that challenge the manufacture industry. The estimation shows the need to make lighter diesel cars that have to be more accessible to all drivers regardless of gender or socioeconomic status. Moreover, the model provides empirical evidence that policies aimed at having more efficient vehicles will increase the intensity of using those cars. Consequently, these policies increase energy consumption and CO_2 emissions. This final conclusion is opposite to the one reached by Al-Hinti et al. (2007), Jeong et al. (2009), and Zervas (2006) who did not use an integral approach. Therefore this paper provides empirical evidence that support Bonilla's (2009) argument that the policy of improving vehicle efficiency as part of the UK's participation in the European Union Voluntary agreement will not be able to achieve its goals of energy consumption and CO_2 mitigation. Additionally, this result supports Frondel et al. (2007) and Schipper et al. (2002)'s argument that when energy services becomes cheaper, it will prompt a rebound effect.

On the other hand, given that despite improvements in public transportation there will be commuters who prefer to travel by car, therefore, a better way to introduce more efficient vehicles in the economy is by combining different policies. Therefore a tax on petrol prices and improvements in public transportation is an effective mitigation policy. However, this policy has to be reinforced with other policies such as keeping a differential price between petrol and diesel and introducing a mechanism like the *French Bonus* to reduce the number of heavy vehicles. An issue for further research is to include in the model a scrap module to estimate more accurate flows in vehicle stock and fuel consumption and CO_2 emissions coming from motorcycles and buses.

[32] A subsidy designed by the French government to increase low CO_2 emissions vehicles.

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