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The Distributional Impacts of Environmental Reforms on Private Transportation in Ireland

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Abstract: This paper provides the first empirical estimation of cross-price elasticities of public and private transportation using a fully flexible demand system and Irish data. Focusing on vehicle owners, in line with the existing literature, the results show that these commodities are complements. This paper also finds that additional carbon taxation is not as regressive as previously found, when the externality cost associated with driving is included in the metric of the tax incidence. A lump-sum transfer and subsidies for public transit can reduce the disproportional burden imposed on low-income households by the carbon tax. However, it is shown that subsidies need to be targeted because benefits are not accrued disproportionally by low-income households, and this can reduce environmental savings from carbon taxes.

I INTRODUCTION

Reducing greenhouse gas (GHG) emissions from the transport sector is a priority in many countries. In Europe, GHG emissions from transport accounted for 25 per cent of total emissions in 2017, while in Ireland the situation is similar. For example, in 2018, 60 per cent of GHG emissions were energy-related emissions and transportation accounted for 40 per cent of this. Carbon taxation is an important policy instrument that can be used to reduce energy demand in the private transport sector. While the distributional effects of carbon taxes in the transport sector have

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received considerable attention in the literature (Poterba, 1991; West, 2004; 2005; Fullerton and West, 2000), existing research mostly analyses energy demand for car travel alone, neglecting the interaction between the demand for this and other commodities, such as public transportation. For example, little attention has been paid in the economics literature to the estimation of cross-price elasticities between public and private transportation. This article provides new insights to the current debate about decarbonising the transport sector by quantifying changes in the distance driven when implementing additional carbon taxes and subsidies for public transportation.

In previous literature, Salvucci *et al.* (2019) found that under a carbon tax, car travel is mainly substituted by rail and non-motorised modes. Cheng *et al.* (2015) investigated the environmental effects of carbon taxes, subsidies for public transportation and investment in infrastructure for motorcycle parking. The authors provided evidence that carbon taxes and motorcycle parking management policies have the largest emissions savings. It is unclear, however, which household types will reduce their demand for car travel. This information can help policymakers to tailor policies to promote public transportation. Thus, to fill this gap in the literature, this article estimates cross-price elasticities for private and public transportation for low- and high-income drivers.

In Ireland, there are important policies to promote the use of public transportation. For instance, implementing major sustainable-mobility projects such as the expansion of the Dublin Area Rapid Transit (DART), Metro Link, and the Bus Connects Programme are important elements in the Irish Climate Action Plan. Bus Connects targets a 50 per cent increase in bus passenger numbers over the lifetime of the project in the country's major cities by investing in infrastructure to increase safety and comfort when travelling. In addition, carbon taxation in Ireland will be gradually increasing. In 2021, the tax passed from €26 per tonne to €33.50 per tonne and it is expected that it will reach €100 per tonne by 2030 (IGEES, 2019). Empirical evidence shows that carbon taxes impose a disproportional burden on low-income households, though the regressive nature of the tax can be overcome by revenue recycling policies (Bento *et al*., 2009). However, carbon taxation alone will not be able to reduce emissions at the level required by the Paris Agreement. In this regard, Wijkander (1985) proposed the idea that complements or substitutes for externality-creating goods can also be taxed or subsidised to reduce externalities. Within this context, changes in driving behaviour and in the income distribution are examined in this article by simulating subsidies for public transportation. Regarding the tax incidence, Tovar Reaños (2020) showed that including externality costs can reduce the tax incidence. It is also argued that, currently, taxes on fuels used in private transportation do not reflect the externalities (e.g. local pollution, congestion, accidents, etc.) caused by vehicle use (Parry, 2015). In order to investigate this further, changes in the tax incidence are analysed when the externality cost is also included.

The environmental benefits of using public transportation are well documented in the literature. Sun *et al*. (2019) found that increases in public transportation can improve the air quality in China. Yang *et al*. (2018) found that with each new subway opening in Beijing, vehicle congestion drops sharply. However, research on the effectiveness of policy instruments to promote the use of public transportation is uncommon. In the same vein, the distributional effects of subsidies for the use of public transportation needs more research. Beaudoin and Lin-Lawell (2018) found that an increase of 10 per cent in infrastructure for public transportation in the US over the years 1991-2011 led to an increase in auto travel of 0.4 per cent. Regarding the distributive effects of subsidies for public transit, Borjesson *et al*. (2020) found that subsidies for public transportation are not effective as a redistribution policy in Stockholm. The same conclusion was reached by Bureau and Glachant (2011) using French data. Bhuvandas and Gundimeda (2020) suggested supporting the use of public transportation to reduce the incidence of carbon taxes.

In this article, changes in welfare are quantified under a scenario of carbon taxes on fuel for private transportation and subsidies for public transportation. In addition, the distributional effects of the implementation of this policy instrument are analysed. To the best of my knowledge, this article is the first study that uses a fully flexible demand system approach to quantify substitution between private and public transportation. This approach allows for quantifying changes in energy demand for private transportation while considering cross-price effects associated with changes in the price of other commodities. Unlike previous studies, the methodology used here does not impose any 'shape' when modelling the relationship between consumption and income. The data used come from the Irish Household Budget Survey (HBS) which reports expenditures on different commodities as well as household mileage. Emissions intensities are also estimated at household level to quantify the externality cost associated with driving, while changes in income inequality are also estimated under a scenario with carbon tax, revenue recycling and subsidies for public transportation.

In terms of the methodology adopted, a demand system represents the demand for different commodities as a function of total expenditure and commodity prices and basically represents 'Engel curves' that describe how household expenditure on a particular commodity changes across different levels of income. The existing literature generally assumes either linear (Deaton and Muellbauer, 1980) or quadratic Engel curves (Banks *et al*., 1997) and while there are numerous studies that use a demand system to analyse the distributional effects of carbon pricing (Baker *et al*., 1989; Labandeira and Labeaga, 1999; Tiezzi and Verde, 2016; Bohringer *et al*., 2017; Tovar Reaños and Wölfing, 2018), few studies focus on the distributional effects of increasing taxes via fuel prices for private transportation. Tiezzi and Verde (2016) assume quadratic Engel curves and find that changes in petrol taxes have significantly greater impacts on petrol demand than marketinduced changes in petrol prices. They include public transportation in their estimation and find that these commodities are complements. The Exact Affine Stone Index (EASI) implicit Marshallian demand system proposed by Lewbel and Pendakur (2009) is a fully flexible demand system, and it is used in this article.

In summary, the contribution of this article to the literature is as follows. First, it provides the first estimation of the incidence of carbon taxes taking into account substitution effects (e.g. public and private transportation) using a fully flexible demand system. In particular, the EASI demand system is employed to allow for flexibility when modelling the relationship between consumption and total expenditure at household level. Second, patterns of substitution of car travel for public transportation and emissions intensities of vehicle ownership are analysed. With this information, the tax incidence is computed when the externalities of driving are considered. Finally, this article also quantifies the environmental and distributional effects of a lump-sum transfer and subsidies for public transportation.

In terms of key findings, the estimated cross-price elasticities show that private and public transportation are complementary commodities and this relationship is stronger for households in the fourth expenditure quartile. It is also found that more affluent households have the largest average CO_2 emissions per kilometre due to low energy efficiency levels. Regarding welfare losses, it is found that the tax is regressive, but recycling carbon taxation revenues can mitigate these regressive effects. Regressivity decreases considerably when the costs associated with the externalities of driving are taken into account. In addition, subsidies for public transportation need to be targeted to reach vulnerable households.

II METHODOLOGY

2.1 The Exact Affine Stone Index (EASI) Implicit Marshallian Demand System

The methodology employed here is similar to that of Tovar Reaños and Wölfing (2018) where after estimating the EASI demand system from microdata, changes in welfare at the household and aggregate level are estimated. The EASI provides a first-order approximation of an arbitrary expenditure function from which a demand system can be derived, and the estimated expenditure function must have all the properties that hold for a theoretical expenditure function (Varian, 1992). First, the expenditure function increases in prices; second, if all commodity prices double, the total expenditure doubles too (homogeneity of degree one in prices); third, indifference curves between goods must be convex to allow for a unique optimal consumption bundle (Shephard's lemma).

The EASI demand system proposed by Lewbel and Pendakur (2009) has been applied to estimate a household demand system. In particular, the authors proposed the following expenditure function:

$$C(p, u, z, \varepsilon) = y_h + \Sigma_{i=1}^{I} m_{ih} \log (p_{ih}) + \frac{1}{2} \Sigma_{i=1}^{I} \Sigma_{j=1}^{I} a_{ij} \log (p_{ih}) \log (p_{jh}) + \frac{1}{2} \Sigma_{i=1}^{I} \Sigma_{j=1}^{I} b_{ij} \log (p_{ih}) \log (p_{jh})\, y_h + \Sigma_{i=1}^{I} \varepsilon_{ih} \log (p_{ih}) \quad (1)$$

where p_{ih} is the price of commodity i and household h, y_h is the implicit household utility and ε_{ih} is the error term. The function m_{ih} is the source of flexibility when modelling Engel curves and defined as:

$$m_{ih} = \Sigma_{r=0}^{R} b_{ir} \log (y_h)^r + \Sigma_{k=1}^{K} [d_{ik} z_{kh} \log (y_h) + g_{ik} z_{kh}] \quad (2)$$

where z_{kh} is the demographic characteristic k of household h and the polynomial degree R is chosen by the modeller. After applying Shephard's lemma to Equation (1), Lewbel and Pendakur (2009) obtain the following function for the budget share:

$$w_{hi} = \Sigma_{r=0}^{R} b_{ir} \log (y_h)^r + \Sigma_{j=1}^{I} a_{ij} \log (p_{ih}) + \Sigma_{j=1}^{I} b_{ij} \log (p_{ih}) \log (y_h) + \Sigma_{k=1}^{K} [d_{ik} z_{kh} \log (y_h) + g_{ik} z_{kh}] + \varepsilon_{ih} \quad (3)$$

with the parameters a_{ij}, b_{ij}, and g_{ik} to be estimated. Using Equations (1), (2) and (3), one can obtain the functional form for the indirect utility function as follows:

$$y_h = \frac{\log (X_h) - \Sigma_{i=1}^{I} w_{ih} \log (p_{ih}) + \frac{1}{2} \Sigma_{i=1}^{I} \Sigma_{j=1}^{I} a_{ij} \log (p_{ih}) \log (p_{jh})}{1 - \frac{1}{2} \Sigma_{i=1}^{I} \Sigma_{j=1}^{I} b_{ij} \log (p_{ih}) \log (p_{jh})} \quad (4)$$

where X_h is the household total expenditure. Note that Pendakur (2008) called this specification a two-way interaction for commodity prices (i.e. p_{ih}) and the indirect utility function (i.e. y_h).

The EASI demand system (3)-(4) is very flexible and allows for non-homothetic preferences and non-linear Engel curves with underlying preferences. The budget shares in (3) depend on various powers of the log of total consumer expenditure and consumer prices. Thus, Engel curves need not be linear but can be concave or convex and can slope down or upwards. The following constraints for homogeneity and Slutsky symmetry are imposed to the parameters:

$$\Sigma_{i=1}^{I} b_{i0} = 1,\ \Sigma_{i=1}^{I} \Sigma_{k=1}^{K} g_{ik} = 0,\ \Sigma_{i=1}^{I} \Sigma_{k=1}^{K} d_{ik} = 0,\ \Sigma_{i=1}^{I} \Sigma_{r=1}^{R} b_{ir} = 0,\ a_{ij} = a_{ji},$$
$$\Sigma_{j=1}^{I} a_{ij} = 0,\ i = 1,\dots, I \text{ and } b_{ij} = b_{ji},\ \Sigma_{j=1}^{I} b_{ij} = 0,\ i = 1,\dots, I.$$

After imposing these restrictions and choosing the last commodity as numeraire, the estimated functions for the budget share are:

$$w_{hi} = \Sigma_{r=0}^{R} b_{ir} \log (y_h)^r + \Sigma_{j=1}^{I-1} a_{ij} \log \left(\frac{p_{ih}}{p_{Ih}}\right) + \Sigma_{t=1}^{T}\Sigma_{j=1}^{I} a_{ijt} \log \left(\frac{p_{ih}}{p_{Ih}}\right) D_t +$$
$$\Sigma_{j=1}^{I-1} b \log \left(\frac{p_{ih}}{p_{Ih}}\right) \log (y_h) + \Sigma_{t=1}^{T}\Sigma_{j=1}^{I} b_{ijt} \log \left(\frac{p_{ih}}{p_{Ih}}\right) \log (y_h) D_t + \quad (5)$$
$$\Sigma_{k=1}^{K} [d_{ik} z_{kh} \log (y_h) + g_{ik} z_{kh}] + \varepsilon_{ih}$$

Note that this specification extends the model used by Tovar and Wölfing (2018) by introducing time dummies D_t and including a two-way interaction between commodity prices and the indirect utility function. Three dummy variables are included to cover the periods considered i.e. 1999-2000, 2005-2010, and 2015-2016.

In this paper, the parameters are estimated using three-stage least squares (3SLS). As in West and Williams (2007) an inverse Mills ratio is computed to correct for the bias introduced by excluding households without a car in the sample. A two-step version of the Heckman correction procedure is used. In the first stage, a probit model on the dichotomous choice to own a vehicle is estimated to calculate the inverse Mills ratio for each household. In the second stage, the estimated ratio is introduced in each of the equations in the demand system estimation. The probit model includes as independent variables whether there are dependent children in the household, the town size, whether there is a garage in the dwelling, and the logarithm of the public transfers received by the households.

The approach in Lewbel (1989) is followed to create more variation in commodity prices and further improve identification of associated parameters. Following Lewbel and Pendakur (2009) and Tovar and Wölfing (2018), uncompensated own-price elasticities (*OPE*), cross-price elasticities (CPE) and expenditure elasticities (*EE*) are computed as follows:

$$E_{piqj}^{cross\ price} = \frac{\partial w_i}{\partial \log (p_j)} * \left(\frac{1}{w_i}\right) for\ i \neq j,$$
$$E_{piqi}^{own\ price} = \frac{\partial w_i}{\partial \log (p_i)} * \left(\frac{1}{w_i}\right) - 1\ for\ i = j \text{ and} \quad (6)$$
$$E_{x}^{expenditure} = \frac{\partial w_i}{\partial \log (Total\ Expenditure)} * \left(\frac{1}{w_i}\right) + 1$$

Standard errors are computed by using bootstrap methods and a Monte Carlo estimation routine is used as in West and Williams (2007)[1] using 100 repetitions. This number of replications can produce reliable estimates of standard errors (see Mooney and Duval, 1993).

We can describe the impacts of changes in welfare by estimating Hicks's equivalent variation (HEV). Following Mas-Colell *et al.* (1995), HEV is defined

[1]See Horowitz (2001) for technical details of the implementation.

as follows: C(p0, U1) – C(p0, U0), where U is the level of household utility and C(*) is the expenditure function, and the indices 0 and 1 represent the initial and post-tax periods.[2] This implies:

$$HEV = \exp\{\Sigma_{i=1}^{I} w_{0i} \log(p_{0i}) - k\Sigma_{i=1}^{I} w_{1i} \log(p_{1i}) - \frac{1}{2}\Sigma_{i=1}^{I}\Sigma_{j=1}^{I} a_{ij} \log(p_{0i}) \log(p_{0j}) - \frac{1}{2} k \Sigma_{i=1}^{I}\Sigma_{j=1}^{I} a_{ij} \log(p_{1i}) \log(p_{1j}) + k \log(X_1)\} - X_0 \quad (7)$$

where $k = \dfrac{1 - \frac{1}{2}\Sigma_{i=1}^{I}\Sigma_{j=1}^{I} b_{ij} \log(p_{i0}) \log(p_{j0})}{1 - \frac{1}{2}\Sigma_{i=1}^{I}\Sigma_{j=1}^{I} b_{ij} \log(p_{i1}) \log(p_{j1})}$.

'Equivalent income' (*xe*) is the income level required to achieve the utility that prevails under the current income level, but at a different set of prices. Note that this definition is distinct from an unrelated definition of equivalent income that appears elsewhere in the economics literature, namely that of a measure of income by a household member that accounts for household composition and economies of scale. Note also that while under a carbon tax $X_0 = X_1$, under a revenue recycling policy after tax, $X_0 \neq X_1$. Tovar Reaños and Wölfing (2018) show that *xe* can be estimated as $x^e =$ *Total Expenditure-Hicks Equivalent Variation*. In my simulation exercise, a Gini coefficient is calculated to analyse changes in the distribution of equivalent income (Tovar Reaños and Wölfing, 2018).

2.2 Tax Revenues, Emissions and Driving Behaviour

To estimate the revenues from carbon taxation, I follow West (2004) where the government has the budget constraint represented in Equation (8). The right-hand side represents the additional revenues raised by the carbon tax on fuel used in private transportation, where p_0, p_1 and Q_1 are the prices and quantities before and after tax. The left-hand side of this equation represents the lump-sum transfers. The demand system is used to provide changes in consumption patterns after taxes for each household.

$$\Sigma_{h=1}^{N} Transfers_h = \Sigma_{h=1}^{N} (p_{1\,priv.transpor} - p_{0\,priv.transpor}) * Q_{1\,priv.transpor,\,h} \quad (8)$$

The level of CO_2 emissions associated with private transportation is estimated using the 2016 wave of the Household Budget Survey (HBS). Weekly fuel expenditure is translated into CO_2 emissions using fuel prices and emissions factors provided by the Sustainable Energy Authority of Ireland

[2] Note that Creedy and Sleeman (2006) and Tovar Reanos and Wolfing (2018) defined HEV as C(p0, U0) – C(p0, U1). This only changes the sign of the HEV. I prefer my definition because welfare changes after tax can be negative, and this has a more intuitive interpretation.

(SEAI). Emission factors and energy prices used in the estimation are displayed in Table 1. The simulated carbon tax only considers direct emissions embedded in the consumption of petrol and diesel and does not consider the effects of carbon taxation on fuels used for heating. Table 1 also provides the prices of petrol and diesel. They are weighted averages estimated with the HBS for the years 2015 and 2016 using information provided by the SEAI.

Table 1: Emission Factors and Fuel Prices

Fuel	*Emissions (g CO_2/kWh)*	*Price (€/kWh)*
Petrol	252.0	0.144
Diesel	264.0	0.121

Source: Data sourced from SEAI (2018) and directly from SEAI.

2.3 Externality Cost of Driving

The cost associated with driving is computed using the costs in euro per kilometre provided by van Essen *et al*. (2019). They provide costs for air pollution, climate change, noise and the costs associated with producing petrol and diesel. The values are provided for diesel and petrol cars in different categories of the ratio CO_2 g/km, have been used in other publications (Tovar Reaños, 2020), and are provided for rural and urban roads.[3] For the cost associated with air pollution, van Essen *et al*. (2019) include damages in health, crop losses, material and building damages (e.g. damages of building facades through particles and dust) and biodiversity loss. As for climate change costs, they are defined as the costs associated with all the effects of global warming, such as sea level rise, biodiversity loss, water management issues, more frequent weather extremes and crop failures. The externality cost at household level is estimated as follows:

$$Externality\ cost_h = \Sigma_{k=1}^{2}\ Emission\ factors * Cost_k/km * wg_k * km_h \qquad (9)$$

where wg_k is the budget share devoted to the purchase of fuel k (i.e. petrol and diesel) and km_h is the distance driven reported in the HBS. wg_k is needed given that the HBS does not provide information on the driven distance broken down by vehicle type. The ratio CO_2 g/km is estimated by dividing the total emissions in the base scenario and the reported annual driven distance in the HBS. The driven distance is estimated as follows:

$$Km = \Sigma_{k=1}^{2}\ Q_h * km\ factor_k \qquad (10)$$

[3] Table A5 in the Appendix provides the mean values of these estimates provided by van Essen *et al.* (2019).

where $km\ factor_h$ is expressed in *km/kWh*. Using the information provided in Table 1, expenditure data on fuels reported by households were translated into energy units.

III DATA

The data used are from the HBS, conducted every five years by the Central Statistics Office (CSO). The purpose of the HBS is to determine a detailed pattern of household expenditures, which in turn is used to update the weighting basis of the Consumer Price Index. The waves from 1994, 1999, 2004, 2009 and 2015-2016 are used in a pooled cross-sectional manner in this article, as are indices for commodity prices for the same years provided by the CSO. For the purpose of this study, the consumption goods were grouped into several categories; food, housing, lighting and heating (which we also term 'heating' throughout the course of this paper), public transportation (i.e. expenditure on bus, train and taxi), private transportation (i.e. petrol and diesel), education and leisure, and other goods and services. Tiezzi and Verde (2016) also use a demand system approach and a similar aggregation to the one used here for public transportation, but this specification excludes an important proportion of the sample. In particular, this aggregation considers only vehicle owners that use public transportation and one of the main drawbacks of using a demand system approach is that it is necessary to exclude zeros in the analysed expenditures. While this is common in the literature (Labandeira *et al*., 2006), using this specification for private and public transportation is very 'exclusive'. This implies a sample selection process where only those that own a vehicle and use public transportation are included in the estimation.

As noted, following West and Williams (2007), I use a Heckman correction procedure to correct for the selection bias,[4] and for the first/main specification I use a sample of 5,957 households – see Table A1 in the Appendix for descriptive statistics. I also perform a robustness check by using the same aggregation, but this time change the public transport aggregation by including expenditures on bus, train, taxi, telephone and internet bills. The sample for this estimation is 16,152 households. While this increases my sample size by reducing the numbers of zeros in this category, it also reduces the size of the share of the expenditure of mobility in the group. Thus, any interpretation of the estimated elasticities for this larger group (i.e. communications plus public transportation) needs to consider that expenditure in communications dominates the expenditure in the group. For instance, changes in the demand for this category as a result of changes in prices represents a change in demand for the entire category, and not only in the demand for public transportation.

[4] The authors use this procedure to estimate demand systems for different combinations of being a vehicle owner and having a single person or a couple working in the household.

My general aggregation strategy is similar to that used in Tovar Reaños and Wölfing (2018) and minimises corner solutions (i.e. zero reported expenditures). It also largely follows the Classification of Individual Consumption According to Purpose (COICOP). As in Baker *et al*. (1989), I do not include the purchase of vehicles and white goods appliances. Instead, dummy variables for ownership of these goods are included e.g. whether the dwelling has gas fired central heating, a washing machine, and dishwasher. Also included are whether a dwelling is in a rural area (according to the CSO classification of same) and the age of the dwelling. In my data around 18 per cent of households do not have a vehicle and vehicle owners have smaller budget shares for the commodities analysed compared to the sample mean. This is because these households expend on average €500 more than the sample mean. Consequently, vehicle owners tend to be distributed between the second and fourth quartiles of the income distribution.

IV MICROSIMULATION DATA AND SCENARIOS

For the purposes of the microsimulation, I use the 2015-2016 HBS because it presents the most recent data available. I simulate the impact of an additional carbon tax of €100 per tonne, which according to Klenert *et al*. (2018) is the level required to reach the goals set in the Paris Agreement. In 2015, the carbon tax in Ireland for non-ETS emissions was €20 per tonne. Consequently, the simulated carbon tax is €120 per tonne on the carbon contained in fuels for private transportation. Note that only vehicle owners are considered in my simulation. Carbon taxes combined with a revenue recycling scheme are also simulated, where the revenue from carbon taxation is distributed via a lump sum payment to each household, colloquially known as a ‘green cheque’. In addition, a subsidy equal to 5 per cent in the price of public transportation is also simulated. Table 2 summarises these scenarios and whether prices or household expenditure effects are expected.

Table 2: Scenario Overview

Scenario	*Description*	*Expenditure change*	*Price change*
NoTax	No increase in tax	NO	NO
Tax	Tax	NO	YES
TaxRev	Tax and lump-sum	YES	YES
Sub	Subsidy for public transportation	NO	YES

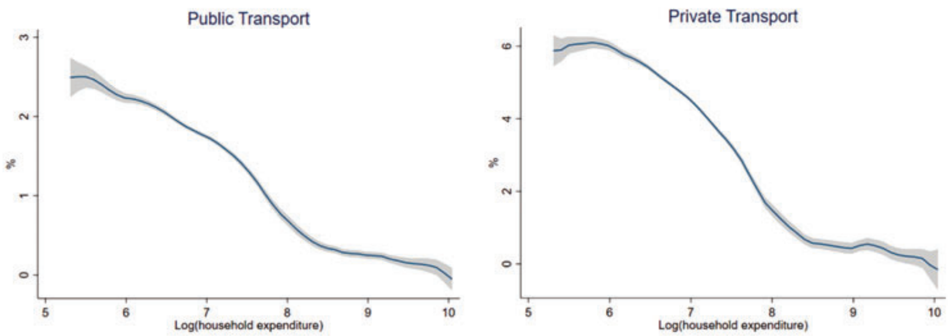
Source: Author's analysis.

V EMPIRICAL RESULTS

5.1 Engel Curves

Figure 1 displays the Engel curves for the estimated budget shares using the EASI demand system for public and private transportation. The Engel curves show that low-income households devote a larger proportion of their income on these commodities than more affluent households.

Figure 1: Estimated Engel Curves



Source: Author's analysis based on the Household Budget Survey.

5.2 Elasticities

The parameters from the demand system described in Equation (5) are presented in Table A2 in the Appendix. Note that in this specification, only car owners that use public transportation are included in the estimation. Higher orders of the polynomial are statistically significant, which indicates that the relationship between expenditure and household income is non-linear. Consequently, the employment of a flexible demand system is justified in this analysis. As highlighted, when analysing the energy consumption of vehicle drivers I am considering only a sub-sample of the data. As a result, it is necessary to correct for this selectivity in the sample. The parameters from the sample selection model are provided in Table A3 in the Appendix. The inverse Mills ratio parameter for the private transportation commodity is statistically significant, which shows that the two-stage process is correcting potential biases in the residuals (see Table A2 in the Appendix).

Tables 3 and 4 display price and expenditure elasticities for the four quartiles of the total expenditure distribution. In general, the size of the estimated own price elasticities for fuels used in private transportation are in line with current studies (e.g. Graham and Glaister, 2002; Goodwin *et al*., 2004; Bureau, 2011; Tovar Reaños, 2020). As for the rest of the own price elasticities, Table A4 in

Table 3: Own- and Cross-Price Elasticities

$\Delta\%\,q$ / $\Delta\%\,p$	*Food*	*Housing*	*Energy*	*Pub. transport*	*Priv. transport*	*Education*	*Services*
				First quartile			
Pub. transport	–0.14**	–0.064	–0.138***	–0.185***	–0.155***	–0.01	–0.105***
	(0.055)	(0.038)	(0.035)	(0.053)	(0.041)	(0.035)	(0.027)
Priv. transport	0.034	0.01	0.02	–0.053***	–0.507***	0.014	–0.007
	(0.038)	(0.024)	(0.016)	(0.016)	(0.034)	(0.020)	(0.020)
				Second quartile			
Pub. transport	–0.125***	–0.12***	–0.149***	–0.115**	–0.206***	–0.003	–0.096***
	(0.047)	(0.032)	(0.031)	(0.046)	(0.035)	(0.031)	(0.027)
Priv. transport	0.067**	0.012	0.009	–0.07***	–0.569***	–0.015	0.007
	(0.030)	(0.018)	(0.012)	(0.013)	(0.025)	(0.017)	(0.019)
				Third quartile			
Pub. transport	–0.117***	–0.177***	–0.139***	–0.143***	–0.229***	0.008	–0.092***
	(0.044)	(0.036)	(0.031)	(0.042)	(0.035)	(0.034)	(0.028)
Priv. transport	0.095***	0.012	–0.001	–0.091***	–0.574***	–0.029	0.015
	(0.033)	(0.019)	(0.014)	(0.015)	(0.026)	(0.021)	(0.023)
				Fourth quartile			
Pub. transport	–0.271**	–0.463***	–0.15	–0.075	–0.383***	0.172	–0.196***
	(0.117)	(0.080)	(0.080)	(0.112)	(0.093)	(0.101)	(0.072)
Priv. transport	–0.002	–0.048	–0.066	–0.156***	–0.791***	0.178***	–0.014
	(0.076)	(0.051)	(0.046)	(0.039)	(0.074)	(0.065)	(0.057)

Source: Author's analysis based on the Household Budget Survey. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in brackets.

Table 4: Expenditure Elasticities

	Food	*Housing*	*Energy*	*Pub. transport*	*Priv. transport*	*Education*	*Services*
First quartile	0.765*** (0.047)	0.894*** (0.089)	0.161** (0.062)	0.797*** (0.092)	0.49*** (0.080)	0.889*** (0.163)	1.715*** (0.138)
Second quartile	0.811*** (0.039)	0.662*** (0.073)	0.203*** (0.054)	0.815*** (0.077)	0.559*** (0.065)	1.377*** (0.099)	1.311*** (0.085)
Third quartile	0.863*** (0.040)	0.527*** (0.069)	0.226*** (0.056)	0.888*** (0.079)	0.573*** (0.073)	1.423*** (0.084)	1.204*** (0.070)
Fourth quartile	1.143*** (0.072)	–0.051 (0.138)	0.392*** (0.123)	1.367*** (0.193)	0.899*** (0.139)	0.968*** (0.076)	1.238*** (0.064)

Source: Author's analysis based on the Household Budget Survey. *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in brackets.

the Appendix provides the full set of elasticities for the four quartiles, and elasticities for energy are in line with estimates found in the literature (see Pothen and Tovar Reaños, 2018; Salotti *et al*., 2015). Regarding the expenditure elasticities presented in Table 4, Clements *et al*. (2006) study expenditure elasticities for 45 different OECD countries and report their average expenditure elasticity for transport as 1.58 for Ireland. My estimates are not directly comparable because unlike Clements *et al*. (2006), I distinguish between public and private transportation. One can see that my estimates for public and private transportation at the high quartile are 1.4 and 0.9 respectively.

The various elasticities for private transportation are displayed in Table 3. The row for private transportation in this table shows the percentage change in quantity demanded of food, housing, energy, public and private transportation, education, and services when there is a 1 per cent increase in the price of private transportation. We can see at the intersection of the row and column: *Priv. transport* and *Pub. Transport* that in the face of higher fuel prices for private transportation, households will show a slight reduction in public transportation. This effect increases for households in the fourth quartile. These findings are in line with Tiezzi and Verde (2016) who also used a demand system approach. Table 3 also shows cross-price elasticities for public and private transportation. One can see that increases in the price of public transportation will decrease the demand for private transportation. This effect is larger for high income households. We can also see that the own price elasticity for vehicle owners in the fourth expenditure quartile is not statistically significant. This suggests that the demand of public transportation for this group is irresponsive to changes in prices. As for expenditure elasticities, we see in Table 4 that public transportation and petrol and diesel are necessity commodities for low income households. This is because expenditure elasticities are not greater than one. Consequently, increases in the price of these commodities will impose a disproportional burden on low income households. When the commodities are necessity goods, Duclos *et al*. (2014) show that an increase in the price can increase income poverty.

In order to explore the robustness of my estimates, a demand system is estimated in which the expenditure of communications is included in the public transportation category. One can see in Table 5 that while the elasticities are slightly larger in absolute value than my previous estimates, the conclusion of complementarity between public and private transportation still holds for this specification. Note that in the case of changes in the price of public transportation, cross-price elasticities for the demand of private transportation are weaker than in the previous specification.

Table 6 shows that expenditure elasticities are smaller and public and private transportation are necessary commodities across income quartiles.

Table 5: Own- and Cross-Price Elasticities: Public Transportation Plus Communications

$\Delta\%$ q / $\Delta\%$ p	*Food*	*Housing*	*Energy*	*Pub. transport*	*Priv. transport*	*Education*	*Services*
				First quartile			
Pub. transport	0.108***	–0.008	–0.041**	–0.439***	–0.117***	0.074***	0.015
	(0.033)	(0.019)	(0.019)	(0.025)	(0.023)	(0.012)	(0.021)
Priv. transport	0.082***	0.036**	0.036***	–0.07***	–0.492***	–0.014	0.033**
	(0.024)	(0.016)	(0.012)	(0.013)	(0.021)	(0.010)	(0.016)
				Second quartile			
Pub. transport	0.063***	–0.036***	–0.07***	–0.465***	–0.116***	0.042***	0.002
	(0.021)	(0.013)	(0.012)	(0.017)	(0.014)	(0.008)	(0.015)
Priv. transport	0.075***	0.03**	0.027***	–0.078***	–0.503***	–0.037***	0.034***
	(0.017)	(0.014)	(0.009)	(0.010)	(0.014)	(0.008)	(0.012)
				Third quartile			
Pub. transport	0.056***	–0.063***	–0.081***	–0.485***	–0.115***	0.045***	0.011
	(0.018)	(0.013)	(0.011)	(0.017)	(0.012)	(0.008)	(0.014)
Priv. transport	0.085***	0.008	0.025**	–0.085***	–0.519***	–0.048***	0.041***
	(0.018)	(0.016)	(0.010)	(0.009)	(0.015)	(0.009)	(0.012)
				Fourth quartile			
Pub. transport	0.012	–0.154***	–0.104***	–0.533***	–0.135***	0.177***	–0.003
	(0.037)	(0.024)	(0.025)	(0.032)	(0.026)	(0.021)	(0.021)
Priv. transport	0.085	–0.069**	0.028	–0.113***	–0.568***	0.035	0.019
	(0.045)	(0.034)	(0.024)	(0.023)	(0.039)	(0.027)	(0.024)

Source: Author's analysis based on the Household Budget Survey. *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in brackets.

Table 6: Expenditure Elasticities: Public Transportation Plus Communications

	Food	*Housing*	*Energy*	*Pub. transport*	*Priv. transport*	*Education*	*Services*
First quartile	0.449***	0.786***	0.001	0.408***	0.39***	1.158***	2.434***
	(0.048)	(0.092)	(0.053)	(0.081)	(0.060)	(0.232)	(0.140)
Second quartile	0.556***	0.587***	0.067	0.581***	0.453***	1.873***	1.675***
	(0.032)	(0.050)	(0.042)	(0.046)	(0.039)	(0.124)	(0.073)
Third quartile	0.627***	0.486***	0.108**	0.633***	0.492***	1.828***	1.414***
	(0.030)	(0.043)	(0.043)	(0.038)	(0.037)	(0.082)	(0.049)
Fourth quartile	0.775***	0.131**	0.363***	0.74***	0.584***	1.308***	1.283***
	(0.042)	(0.062)	(0.076)	(0.056)	(0.063)	(0.061)	(0.040)

Source: Author's analysis based on the Household Budget Survey. *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in brackets.

5.3 Welfare Changes at Household Level

Table 7 shows the estimated Hicks Equivalent Variation (HEV) for vehicle owners relative to total expenditure for three types of households. Households in retirement age, single parents, and households with children in the lowest expenditure level are the most affected by the tax. We can also see that when the revenues are allocated equally among households, the most vulnerable groups are compensated. In the last scenario, we can see the welfare changes due to the subsidies on public transportation. It suggests that the benefits are homogeneously distributed across income quartiles. Note that for single people in retirement age with children in high income quartiles, I do not have units in my sample to identify their welfare changes.

Table 7: HEV Relative to Total Expenditure (%)

	1st quartile	*2nd quartile*	*3rd quartile*	*4th quartile*
		Tax		
Single +65	–1.317	–0.281		
Single with children	–1.416	–0.629	–0.367	
2 adults with children	–1.217	–1.040	–0.773	–0.625
All households	–1.157	–1.007	–0.792	–0.614
		TaxRev		
Single +65	0.248	0.544		
Single with children	0.983	0.372	0.296	
2 adults with children	0.392	–0.087	–0.105	–0.188
All households	0.588	–0.028	–0.112	–0.177
		TaxSub		
Single +65	–1.174	–0.242		
Single with children	–1.336	–0.634	–0.418	
2 adults with children	–1.144	–1.024	–0.743	–0.601
All households	–1.069	–0.944	–0.731	–0.569

Source: Author’s analysis based on the Household Budget Survey.

Table 8 displays the estimates for the model where communications is incorporated into the public transportation expenditure category. It shows again that the welfare change after tax for these households is above the mean (i.e. scenario ‘Tax’). Under the revenue recycling mechanism, I find that poor households disproportionally benefit but under the second scenario, we can again see a flat distribution of benefits.

Figure 2 summarises estimated welfare losses for rural and urban households, suggesting that carbon taxes impose a larger burden on rural households than on urban ones. In the analysed sample, while the mean daily driven distance is

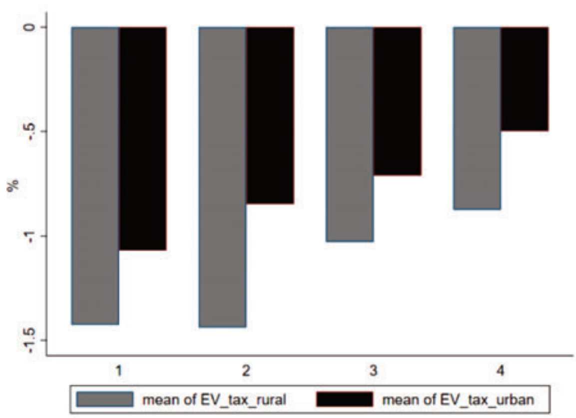
Table 8: HEV Relative to Total Expenditure (%): Public Transportation Plus Communications

	1st quartile	*2nd quartile*	*3rd quartile*	*4th quartile*
		Tax		
Single +65	–1.583	–0.776	–0.649	–0.141
Single with children	–1.738	–1.099	–0.543	–0.516
2 adults with children	–1.563	–1.289	–0.953	–0.706
All households	–1.544	–1.234	–0.989	–0.756
		TaxRev		
Single +65	1.526	0.516	0.535	0.440
Single with children	1.093	0.263	0.310	0.090
2 adults with children	0.640	0.036	–0.105	–0.182
All households	1.020	0.121	–0.124	–0.222
		TaxSub		
Single +65	–1.351	–0.697	–0.530	–0.106
Single with children	–1.503	–0.966	–0.397	–0.325
2 adults with children	–1.324	–1.089	–0.810	–0.589
All households	–1.296	–1.026	–0.806	–0.603

Source: Author's analysis based on the Household Budget Survey.

61 km in rural Ireland, urban households drive around 45 km. Difference in the provision of public transportation in rural and urban areas has been identified as a barrier to transit towards a more sustainable transportation system in Ireland (see Browne *et al*., 2011).

Figure 2: HEV Relative to Expenditure for Rural and Urban Households



Source: Author's analysis based on the Household Budget Survey.

5.4 Welfare Changes and the Cost of Pollution

Figure 3 displays the ratio of emissions per kilometre for diesel and petrol vehicles across expenditure levels. This shows that higher income groups have larger levels of pollution regarding vehicle use. Similarly, Tovar Reaños (2020) found that large vehicles have larger CO_2 emissions compared to other vehicle types. If more affluent households have preferences for large vehicles that potentially have larger emissions ratios per household in rural Ireland, carbon taxes on fuel prices need to be jointly designed with other policies such as motor and registration taxes. In Ireland, the registration tax and motor tax were changed in July 2008 from engine size to carbon emissions. These taxes are based on vehicle emissions rather than emissions at the household level. This distinction becomes relevant when households own more than one vehicle. While the HBS does not provide information on the type of vehicle owned by the household, I can make some inference based on the expenditures on petrol and diesel reported in the data. Table 9 shows the distribution of vehicle ownership, and one can see that households that own a single vehicle represent 52 per cent of the sample. Among those, 65 per cent report expenditure only on petrol. Regarding households that own more than two vehicles, 35 per cent report expenditure in both petrol and diesel. Emission levels will be the result of a combination of the intensity of use and the vehicle type. Figure 3 shows that petrol cars have a lower ratio of emissions per kilometre and these vehicle types are still in the majority for single vehicle owners. However, the picture is unclear for owners of more than one vehicle.

Table 9: Vehicle Ownership Distribution (%)

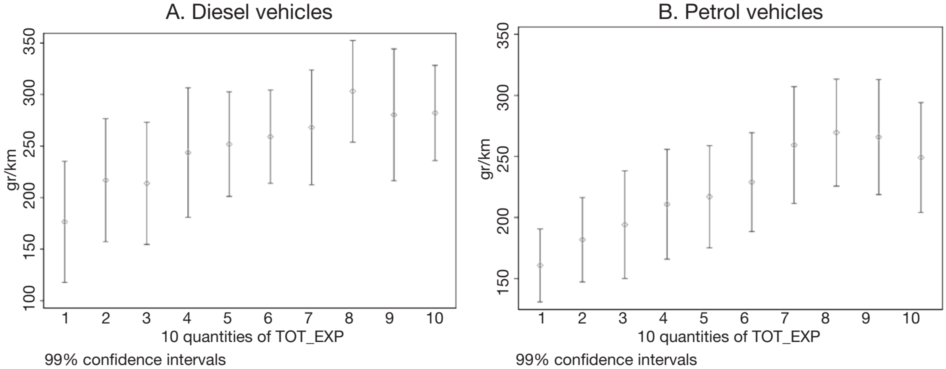
	Petrol	*Diesel*	*Both*	*Sample*
One vehicle	0.651	0.349	0.000	0.517
More than one	0.416	0.230	0.354	0.483

Source: Author's analysis based on the Household Budget Survey.

Figure 4 presents the mean externality cost across expenditure levels, with values equivalised by household size. It shows that the cost increases for more affluent households.

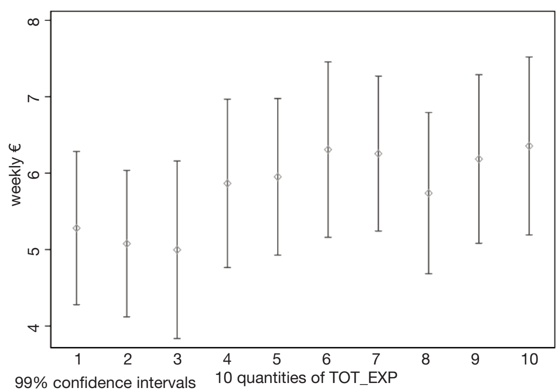
Figure 5 shows the incidence using the Hicks Equivalent Variation when externality costs associated with driving are taken into account. It shows that the incidence reduces significantly across all expenditure levels. The change in the incidence is particularly important for the first two deciles. Increase in fuel prices used in private transportation via carbon taxes is a policy instrument that can internalise the externalities associated with the vehicle usage. Figure 5 shows that considering the externality cost associated with driving can reduce the tax incidence of carbon taxes.

Figure 3: Household-Emissions per km for Diesel and Petrol Vehicles



Source: Author's analysis based on the Household Budget Survey.

Figure 4: Externality Cost

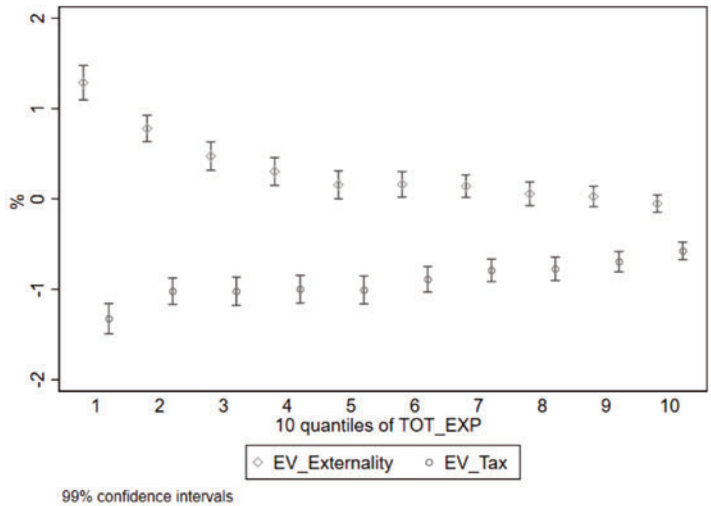


Source: Author's analysis based on the Household Budget Survey.

5.5 Aggregate Effects

The first row in Table 10 displays the estimated total weekly emissions and the average kilometres driven for the years 2015-2016. This provides my estimated average for emissions and distance driven per household for one week. The table also provides the revenue collected as a percentage of total expenditure. The following rows display the changes in these variables with respect to the base scenario. One can see that a carbon tax reduces emissions by 8.5 per cent and increases inequality by 0.5 per cent. The revenue-allocation scenario reduces slightly the environmental benefits and the inequality caused by the tax. Using subsidies for public transportation reduces the increase in inequality caused by the tax, but it also reduces the environmental gains. Under this scenario the demand for both private and public transportation is affected (i.e. because of complementarity). In particular, while there is a subsidy of 5 per cent in the price of public transportation, there is an important reduction in environmental

Figure 5: HEV Including and Excluding Externality Costs Relative to Expenditure



Source: Author's analysis based on the Household Budget Survey.

gains. Consequently, a targeted policy needs to be implemented in which low income and rural households should be prioritised.

In the previous section, I showed that the benefits of reducing the price of public transportation do not accrue disproportionally to low-income households. In addition, cross-price elasticities show that the complementarity of public and private transportation is weaker for this group than for more affluent households. It is important to note that I use a sub-sample of vehicle owners for these estimations while, in addition, my estimates come from self-reported data on the distance driven. While accuracy would be improved by using data from odometer readings, there are no available data that combine the socioeconomic information of the driver and the driven distance.

Table 10: Changes in Emissions, Distance Driven and Revenue using the EASI Demand System

	Weekly mean CO_2 emissions (T)	*Weekly mean Km*	*Revenue (%)*	*Gini*
Base	0.088	376.474	0.735	0.243
Δ w.r.t to Base (%)				
Tax	–8.585	–6.576	891.413	0.515
TaxRev	–8.141	–6.162	0.000	–0.263
TaxSub	–7.960	–5.787	0.000	0.492

Source: Author's analysis based on the Household Budget Survey.

Table 11 displays the results from using the model in which expenditure in public transportation and communications are grouped into a single category. It shows that while similar patterns are evident, the changes are larger in all the analysed metrics. In addition, the difference between the last two scenarios is smaller than in my previous analysis.

Table 11: Changes in Emissions, Distance Driven and Revenue using the EASI Demand System: Public Transportation Plus Communications

	Weekly mean CO_2 emissions (T)	*Weekly mean Km*	*Revenue (%)*	*Gini*
Base	0.081	375.893	0.878	0.259
	Δ w.r.t to Base (%)			
Tax	–6.836	–3.863	548.344	0.576
TaxRev	–6.288	–3.358	0.000	–0.452
TaxSub	–6.226	–3.061	0.000	0.489

Source: Author's analysis based on the Household Budget Survey.

VI CONCLUSIONS AND POLICY IMPLICATIONS

A carbon tax is a policy instrument that can internalise the externalities associated with vehicle usage. However, its implementation brings several challenges for policymakers. Setting the level of taxes according to the externality cost is the first challenge. In addition, carbon taxes need to be implemented alongside other policy instruments like subsidies for public transportation in order to reduce emissions. It is important to design policies where drivers that are overcharged by carbon taxes can be compensated, and higher taxes can be implemented for those that are undercharged. Addressing concerns about the distributional effects of the tax can increase public acceptance. Little attention in the economics literature has been paid to the estimation of cross-price effects between public and private transportation. This article provides new insights to the current debate about decarbonising the transport sector by quantifying changes in the distance driven when implementing additional carbon taxes and subsidies for public transportation. The EASI demand system is employed to allow for flexibility when modelling the relationship between consumption and total expenditure at household level. By using Irish data and a highly flexible demand system, cross-price elasticities are estimated for private and public transportation. The results show that these commodities are complements. The estimated changes in distance driven and CO_2 emissions show that a carbon tax is effective in reducing emissions and its distributional impacts can be addressed by a lump-sum transfer. In addition, given the complementarity between public and private transportation, subsidies for public transportation will increase the demand for both commodities. This calls for the design of policies to improve public transportation that help us to pass from a complementary relationship to a substitution one. In this regard, Liu *et al*. (2016) show that attitudes towards public transportation is a factor in supporting this transport modality. In addition, any subsidy scheme needs to be designed to consider all the factors that affect the choice mode of vulnerable groups.

The results in this article show that when the externality cost associated with driving is included when computing the carbon-tax incidence, the regressive effect of the tax reduces sharply. The paper also provides evidence that the tax burden reduces considerably when the externality cost of driving is included in the estimation. While creating awareness of the externality cost associated with driving can increase carbon tax acceptability, there can still be issues with the policies used for the re-allocation of additional revenue. Jiang and Ouyang (2017) argue that targeting low-income households is key to reducing the tax burden on vulnerable households. Political preferences can limit the implementation of a carbon tax and dividend scheme. Jagers *et al*. (2019) found that in a right-oriented context, a combination of a tax and compensatory scheme may have higher social acceptance. In left-oriented contexts, carbon taxes without compensation are more likely to increase support. In practice, tax revenue is not always distributed directly across households. Sumner *et al*. (2011) analysed the use of carbon dividends across different countries, finding that in half of the analysed countries a dividend is used to compensate taxpayers while the remainder use the revenues to support investment in green projects.

I show that the average emissions per kilometre are higher for high income households. This can be associated with the type of vehicle owned by households. I find that the average emissions per kilometre of diesel vehicles are higher than vehicles run on petrol, and that private owners of single vehicles are more likely to own a petrol vehicle. However, this might not be the case for households that own more than one vehicle. Tovar Reaños (2020) found that large vehicles can also have high levels of emissions.

Feebate schemes (e.g. the French 'bonus-malus' system) might help to reduce the demand for heavy polluting vehicles by paying consumers that purchase fuel-efficient vehicles and charging a penalty to those that purchase 'gas-guzzlers'. Harvey (2020) argues that while governments are subsidising the purchase of electric vehicles (EVs), the market share of SUVs and pickup trucks grows. The author suggests improving energy efficiency independently of the penetration of EVs. As to the distributional effects of policies to increase the energy efficiency level in the vehicle stock, offering grants for the purchase of electric vehicles is found to be regressive by Tovar Reaños and Sommerfeld (2018). They found that these grants will increase income inequality as mainly high-income households could afford to purchase them. In addition, for households that can afford more than one vehicle, grants could be indirectly subsidising ownership of a second heavy polluting vehicle. Taxes based on vehicle emissions need to be considered for the emissions at the household level and not only at vehicle level. This calls for a better design and combination of policy instruments to set the right tax for addressing environmental damage and equity issues. A socially accepted policy must combine the 'ability to pay' and "polluter pays" principles.

Finally, it is important to highlight an important limitation of this study i.e. the large number of zeros in expenditure for public transportation reported by vehicle owners. I provide a solution to this by including expenditure in communications in the transportation expenditure category, but it has the largest share of the expenditure in the category. Consequently, the interpretation of the results from this additional analysis needs to be understood in this context.

REFERENCES

Baker, P., R. Blundell and J. Micklewright, 1989. "Modelling household energy expenditures using micro-data", *The Economic Journal*, 99(397):720-738.

Banks, J., R. Blundell and A. Lewbel, 1997. "Quadratic Engel curves and consumer demand", *The Review of Economics and Statistics*, 79(4):527-539.

Beaudoin, J. and C.-Y. C. Lin-Lawell, 2018. "The effects of public transit supply on the demand for automobile travel", *Journal of Environmental Economics and Management*, 88:447-467.

Bento, A.M., L.H. Goulder, M.R. Jacobsen and R.H. von Haefen, 2009. "Distributional and efficiency impacts of increased US gasoline taxes", *American Economic Review*, 99(3): 667-99.

Bhuvandas, D. and H. Gundimeda, 2020. "Welfare impacts of transport fuel price changes on Indian households: An application of LA-AIDS model", *Energy Policy*, 144:111583.

Bohringer, C., F. Landis and M.A. Tovar Reaños, 2017. "Economic Impacts of Renewable Energy Production in Germany", *The Energy Journal*, 0(KAPSARC S).

Borjesson, M., J. Eliasson and I. Rubensson, 2020. "Distributional effects of public transport subsidies", *Journal of Transport Geography*, 84:102674.

Browne, D., B. Caulfield and M. O'Mahony, 2011. *Barriers to sustainable transport in Ireland*. Environmental Protection Agency. CCRP Report.

Bureau, B., 2011. "Distributional effects of a carbon tax on car fuels in France", *Energy Economics*, 33(1):121-130.

Bureau, B. and M. Glachant, 2011. "Distributional effects of public transport policies in the Paris region". *Transport Policy*, 18(5):745-754.

Cheng, Y.-H., Y.-H. Chang and I. Lu, 2015. "Urban transportation energy and carbon dioxide emission reduction strategies", *Applied Energy*, 157:953-973.

Clements, K.W., Y. Wu and J. Zhang, 2006. "Comparing international consumption patterns", *Empirical Economics*, 31(1):1-30.

Creedy, J. and C. Sleeman, 2006. "Carbon taxation, prices, and welfare in New Zealand", *Ecological Economics*, 57(3):333-345.

Deaton, A. and J. Muellbauer, 1980. "An almost ideal demand system", *The American Economic Review*, 70(3):312-326.

Duclos, J.-Y., P. Makdissi and A. Araar, 2014. "Pro-poor indirect tax reforms, with an application to Mexico", *International Tax and Public Finance*, 21(1):87-118.

Fullerton, D. and S. West, 2000. *Tax and subsidy combinations for the control of car pollution*. (7774).

Goodwin, P., J. Dargay and M. Hanly, 2004. "Elasticities of road traffic and fuel consumption with respect to price and income: A review", *Transport Reviews*, 24(3):275-292.

Graham, D.J. and S. Glaister, 2002. "The demand for automobile fuel: A survey of elasticities", *Journal of Transport Economics and Policy*, 36(1):1-25.

Harvey, L.D., 2020. "Rethinking electric vehicle subsidies, rediscovering energy efficiency", *Energy Policy*, 146:111760.

Horowitz J.L., 2001. "The Bootstrap", in J. Heckman and E. Leamer (eds.), *Handbook of Econometrics*, Vol. 5, Elsevier, Amsterdam.

Irish Government Economic and Evaluation Service (IGEES), 2019. "Valuing Greenhouse Gas Emissions in the Public Spending Code". Technical report. Irish Government Economic and Evaluation Service. Available at:
https://assets.gov.ie/19749/77936e6f1cb144d68c1553c3f9ddb197.pdf.

Jagers, S.C., J. Martinsson and S. Matti, 2019. "The impact of compensatory measures on public support for carbon taxation: an experimental study in Sweden", *Climate Policy*, 19(2): 147-160.

Jiang, Z. and X. Ouyang, 2017. "Analyzing the distributional effects of fuel taxation in China", *Energy Efficiency*, 10:1235-1251.

Klenert, D., L. Mattauch, E. Combet, O. Edenhofer, C. Hepburn, R. Rafaty and N. Stern, 2018. "Making carbon pricing work for citizens", *Nature Climate Change*, 8(8):669-677.

Labandeira, X. and J. Labeaga, 1999. "Combining input-output analysis and micro-simulation to assess the effects of carbon taxation on Spanish households", *Fiscal Studies*, 20(3): 305-320.

Labandeira, X., J. Labeaga and M. Rodriguez, 2006. "A residential energy demand system for Spain", *The Energy Journal*, 27(2):87-112.

Lewbel, A., 1989. "Identification and Estimation of Equivalence Scales under Weak Separability", *Review of Economic Studies*, 56(2):311-316.

Lewbel, A. and K. Pendakur, 2009. "Tricks with Hicks: The EASI Demand System", *American Economic Review*, 99(3):827-63.

Liu, Y., Z. Hong and Y. Liu, 2016. "Do driving restriction policies effectively motivate commuters to use public transportation?", *Energy Policy*, 90:253-261.

Mas-Colell A., M.D. Whinston and J.R. Green, 1995. *Microeconomic Theory*. Oxford.

Mooney, C.Z. and D. Duval, 1993. *Bootstrapping: A Nonparametric Approach to Statistical Inference*. Newbury Park, CA: SAGE.

Parry, I., 2015. "Designing fiscal policy to address the external costs of energy", *International Review of Environmental and Resource Economics*, 8(1):1-56.

Pendakur, K., 2008. "EASI made easier", *Contributions to Economic Analysis*. 288. 179-206. Available at: http://www.sfu.ca/~pendakur/EASI%20made%20Easier.pdf.

Poterba, J.M., 1991. *Is the gasoline tax regressive?* Vol. 5:145-164.

Pothen, F. and M.A. Tovar Reaños, 2018. "The distribution of material footprints in Germany", *Ecological Economics*, 153:237-251.

Salotti, S., L. Montinari, A.F. Amores and J.M. Rueda-Cantuche, 2015. "Total expenditure elasticity of non-durable consumption of European households", in JRC Technical Report EUR 27081 EN, page 2015. European Union.

Salvucci, R., M. Gargiulo and K. Karlsson, 2019. "The role of modal shift in decarbonizing the Scandinavian transport sector: Applying substitution elasticities in times-Nordic", *Applied Energy*, 253:113593.

SEAI, 2018. "Energy-related CO2 emissions in Ireland 2005-2016". Sustainable Energy Authority Ireland. https://www.seai.ie/publications/Energy-Emissions-2017-Final.pdf.

Sumner, J., L. Bird and H. Dobos, 2011. "Carbon taxes: a review of experience and policy design considerations", *Climate Policy*, 11(2):922-943.

Sun, C., W. Zhang, X. Fang, X. Gao and M. Xu, 2019. "Urban public transport and air quality: Empirical study of China cities", *Energy Policy*, 135:110998.

Tiezzi, S. and S.F. Verde, 2016. "Differential demand response to gasoline taxes and gasoline prices in the U.S.", *Resource and Energy Economics*, 44:71-91.

Tovar Reaños, M.A., 2020. "Initial incidence of carbon taxes and environmental liability. a vehicle ownership approach", *Energy Policy*, 143:111579.

Tovar Reaños, M.A. and K. Sommerfeld, 2018. "Fuel for inequality: Distributional effects of environmental reforms on private transport", *Resource and Energy Economics*, 51:28-43.

Tovar Reaños, M.A. and N.M. Wölfing, 2018. "Household energy prices and inequality: Evidence from German microdata based on the EASI demand system", *Energy Economics*, 70:84-97.

van Essen, H., L. van Wijngaarden, A. Schroten, D. Sutter, C. Bieler, S. Maffii, M. Brambilla, D. Fiorello, F. Fermi, R. Parolin and K.E. Beyrouty, 2019. *Handbook on the external costs of transport.* Publications of CE Delft.

Varian, H., 1992. *Microeconomic theory*. W. W. Norton & Company, New York.

West, S.E., 2004. "Distributional effects of alternative vehicle pollution control policies", *Journal of Public Economics*, 88(3-4):735-757.

West, S.E., 2005. "Equity implications of vehicle emissions taxes", *Journal of Transport Economics and Policy*, 39(1):1-24.

West, S.E. and R.C. Williams, 2007. "Optimal taxation and cross-price effects on labor supply: Estimates of the optimal gas tax", *Journal of Public Economics*, 91(3):593-617.

Wijkander, H., 1985. "Correcting externalities through taxes on/subsidies to related goods", *Journal of Public Economics.*

Yang, J., S. Chen, P. Qin, F. Lu and A.A. Liu, 2018. "The effect of subway expansions on vehicle congestion: Evidence from Beijing", *Journal of Environmental Economics and Management*, 88:114-133.

APPENDIX: TABLES

Table A1: Summary Statistics

	Mean	*Std. Dev*
Budget shares:		
s1	0.221	0.111
s2	0.136	0.120
s3	0.034	0.024
s4	0.016	0.017
s5	0.042	0.031
s6	0.226	0.183
s7	0.323	0.177
Prices (logs):		
p1	4.233	0.253
p2	3.341	0.457
p3	3.757	0.378
p4	3.451	0.398
p5	3.964	0.343
p6	3.750	0.731
p7	2.722	0.895
Total expenditure	1,566.680	1,929.427
Other controls:		
Rural	0.321	0.467
Dwelling built before 1960	0.229	0.420
Dwelling built between 1960-1980	0.287	0.452
Dwelling built between 1981-2000	0.340	0.474
Central heating Gas	0.243	0.429
Washing machine	0.247	0.431
Dishwasher	0.261	0.439
N		5,957

Source: Author's analysis based on the Household Budget Survey.

Table A2: EASI Demand System; Linear 3 Stage Least Squares Estimation, Estimated from Equation (5). Selected Estimates from Equation (4)

VARIABLES	*Food*	*Housing*	*Heating*	*Pub. Tran*	*Priv. Tran*	*Education*
Polynomial coefficient:						
y1	0.461***	0.478***	–0.024	0.044	0.118**	–1.950***
	(0.139)	(0.171)	(0.032)	(0.032)	(0.049)	(0.208)
y2	–0.205***	–0.150**	–0.01	–0.022*	–0.057***	0.723***
	(0.053)	(0.065)	(0.012)	(0.012)	(0.018)	(0.079)
y3	0.034***	0.017	0.003	0.004*	0.010***	–0.105***
	(0.009)	(0.011)	(0.002)	(0.002)	(0.003)	(0.013)
y4	–0.002***	–0.001	–0.000*	–0.000*	–0.001***	0.005***
	(0.001)	(0.001)	0.000	0.000	0.000	(0.001)
Socioeconomic variables (Base category: z4=Couples with dependent children)						
z1	–0.084***	0.048*	–0.021***	0.006	–0.016**	–0.127***
	(0.022)	(0.027)	(0.005)	(0.005)	(0.008)	(0.033)
z2	–0.078	–0.025	0.01	0.002	–0.040*	–0.555***
	(0.062)	(0.077)	(0.014)	(0.014)	(0.021)	(0.094)
z3	0.012	0.036	0.007	0.003	–0.011	–0.038
	(0.025)	(0.031)	(0.006)	(0.006)	(0.009)	(0.038)
z5	0	–0.003	–0.008**	0	–0.008	–0.062***
	(0.015)	(0.018)	(0.003)	(0.003)	(0.005)	(0.022)
z6	0.065***	–0.067***	–0.003	0.009***	0.003	–0.001
	(0.010)	(0.013)	(0.002)	(0.002)	(0.004)	(0.016)
Interaction terms of y and z (Base category: z4=Couples with dependent children)					–	
yz1	0.012*	–0.007	0.004**	–0.002	0.003	0.045***
	(0.007)	(0.008)	(0.002)	(0.002)	(0.002)	(0.010)

Table A2: EASI Demand System; Linear 3 Stage Least Squares Estimation, Estimated from Equation (5). Selected Estimates from Equation (4) (Contd.)

VARIABLES	*Food*	*Housing*	*Heating*	*Pub. Tran*	*Priv. Tran*	*Education*
yz2	0.015	–0.009	–0.004	0	0.01	0.211***
	(0.021)	(0.026)	(0.005)	(0.005)	(0.007)	(0.032)
yz3	–0.006	–0.014	–0.002	0	0.002	0.016
	(0.008)	(0.010)	(0.002)	(0.002)	(0.003)	(0.012)
yz5	–0.001	–0.001	0.002*	0	0.002	0.019***
	(0.004)	(0.005)	(0.001)	(0.001)	(0.001)	(0.006)
yz6	–0.009***	0.010***	0.001	–0.001*	0	0.003
	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)	(0.004)
Interaction terms ($b_{i,j}$):						
ynp1	–0.027***	0.008**	0.001	0.001	0	0.010**
	(0.004)	(0.003)	(0.001)	(0.001)	(0.002)	(0.004)
ynp2	0.008**	0.005	0	0.003**	0.001	–0.016***
	(0.003)	(0.006)	(0.001)	(0.001)	(0.002)	(0.005)
ynp3	0.001	0	–0.007***	0	–0.001	0.005***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
ynp4	0.001	0.003**	0	–0.007***	0	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ynp5	0	0.001	–0.001	0	–0.009***	0.006***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
ynp6	0.010**	–0.016***	0.005***	0.002	0.006***	–0.062***
	(0.004)	(0.005)	(0.001)	(0.001)	(0.002)	(0.007)
Time variant parameters ($b_{i,t}$):						
ynp1_t1	–0.010***	0.002	0	–0.001	0.002	0.013***
	(0.004)	(0.004)	(0.002)	(0.001)	(0.003)	(0.004)

Table A2: EASI Demand System; Linear 3 Stage Least Squares Estimation, Estimated from Equation (5). Selected Estimates from Equation (4) (Contd.)

VARIABLES	*Food*	*Housing*	*Heating*	*Pub. Tran*	*Priv. Tran*	*Education*
ynp2_t1	0.002	–0.015**	0.002	–0.001	0.001	0.013**
	(0.004)	(0.008)	(0.002)	(0.002)	(0.002)	(0.006)
ynp3_t1	0	0.002	–0.003	0	0.001	–0.002
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
ynp4_t1	–0.001	–0.001	0	0.003	0	–0.001
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
ynp5_t1	0.002	0.001	0.001	0	–0.003	0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)
ynp6_t1	0.013***	0.013**	–0.002	–0.001	0.001	–0.049***
	(0.004)	(0.006)	(0.002)	(0.002)	(0.002)	(0.010)
ynp1_t2	0.012**	–0.004	0.001	0.002	0.008***	–0.018***
	(0.006)	(0.005)	(0.002)	(0.002)	(0.003)	(0.005)
ynp2_t2	–0.004	0	0.004**	–0.007***	0.001	0.031***
	(0.005)	(0.008)	(0.002)	(0.002)	(0.003)	(0.006)
ynp3_t2	0.001	0.004**	–0.006**	0.001	0.002	–0.002
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
ynp4_t2	0.002	–0.007***	0.001	0.006***	–0.001	–0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
ynp5_t2	0.008***	0.001	0.002	–0.001	–0.002	–0.006***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)
ynp6_t2	–0.018***	0.031***	–0.002	–0.001	–0.006***	0.023***
	(0.005)	(0.006)	(0.002)	(0.002)	(0.002)	(0.009)
ynp1_t3	0.019**	–0.011*	0.006**	0	0.009*	–0.014
	(0.009)	(0.006)	(0.003)	(0.003)	(0.005)	(0.009)
ynp2_t3	–0.011*	–0.006	0.003	–0.003	0.002	0.014
	(0.006)	(0.010)	(0.002)	(0.002)	(0.003)	(0.009)

Table A2: EASI Demand System; Linear 3 Stage Least Squares Estimation, Estimated from Equation (5). Selected Estimates from Equation (4) (Contd.)

VARIABLES	*Food*	*Housing*	*Heating*	*Pub. Tran*	*Priv. Tran*	*Education*
ynp3_t3	0.006**	0.003	–0.006*	0.001	–0.002	–0.003
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
ynp4_t3	0	–0.003	0.001	0	0.002	0
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
ynp5_t3	0.009*	0.002	–0.002	0.002	0	–0.010**
	(0.005)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)
ynp6_t3	–0.014	0.014	–0.003	0	–0.010**	0.023
	(0.009)	(0.009)	(0.003)	(0.003)	(0.004)	(0.015)
Price parameter ($a_{i,j,l}$)						
np1	0.074***	–0.066***	–0.006	–0.009**	–0.012	0.048***
	(0.016)	(0.013)	(0.005)	(0.005)	(0.008)	(0.016)
np2	–0.066***	0.002	0	–0.013***	–0.006	0.075***
	(0.013)	(0.022)	(0.005)	(0.005)	(0.008)	(0.019)
np3	–0.006	0	0.036***	–0.003	0.002	–0.016***
	(0.005)	(0.005)	(0.006)	(0.004)	(0.007)	(0.005)
np4	–0.009**	–0.013***	–0.003	0.037***	–0.002	–0.004
	(0.005)	(0.005)	(0.004)	(0.005)	(0.006)	(0.005)
np5	–0.012	–0.006	0.002	–0.002	0.049***	–0.013*
	(0.008)	(0.008)	(0.007)	(0.006)	(0.013)	(0.008)
np6	0.048***	0.075***	–0.016***	–0.004	–0.013*	0.013
	(0.016)	(0.019)	(0.005)	(0.005)	(0.008)	(0.030)
Time variant parameters ($a_{i,j,t}$):						
np1t1	0.045***	(0.008)	(0.001)	0.002	(0.007)	–0.050***
	–0.015	–0.016	–0.006	–0.006	–0.011	–0.017

Table A2: EASI Demand System; Linear 3 Stage Least Squares Estimation, Estimated from Equation (5). Selected Estimates from Equation (4) (Contd.)

VARIABLES	*Food*	*Housing*	*Heating*	*Pub. Tran*	*Priv. Tran*	*Education*
np1t2	(0.009)	0.042**	0.003	(0.004)	(0.012)	(0.019)
	–0.02	–0.018	–0.007	–0.006	–0.01	–0.019
np1t3	(0.037)	0.078***	–0.017*	0.002	(0.023)	(0.032)
	–0.029	–0.021	–0.01	–0.01	–0.016	–0.03
np2t1	(0.008)	0.068**	(0.008)	0.002	(0.010)	–0.050**
	–0.016	–0.03	–0.007	–0.007	–0.01	–0.025
np2t2	0.042**	(0.002)	–0.015**	0.024***	(0.003)	–0.136***
	–0.018	–0.029	–0.007	–0.007	–0.01	–0.023
np2t3	0.078***	0.038	–0.014*	0.014*	(0.005)	–0.085***
	–0.021	–0.034	–0.007	–0.007	–0.011	–0.03
np3t1	(0.001)	(0.008)	0.011	0.000	(0.005)	0.009
	–0.006	–0.007	–0.009	–0.006	–0.009	–0.006
np3t2	0.003	–0.015**	0.023***	(0.003)	(0.004)	(0.002)
	–0.007	–0.007	–0.009	–0.005	–0.008	–0.006
np3t3	–0.017*	–0.014*	0.033***	(0.004)	0.007	0.004
	–0.01	–0.007	–0.011	–0.008	–0.011	–0.009
np4t1	0.002	0.002	0.000	–0.012*	0.003	0.003
	–0.006	–0.007	–0.006	–0.007	–0.008	–0.006
np4t2	(0.004)	0.024***	(0.003)	–0.019***	0.003	0.000
	–0.006	–0.007	–0.005	–0.007	–0.007	–0.006
np4t3	0.002	0.014*	(0.004)	0.005	(0.010)	(0.004)
	–0.01	–0.007	–0.008	–0.011	–0.011	–0.01
np5t1	(0.007)	(0.010)	(0.005)	0.003	0.016	(0.001)
	–0.011	–0.01	–0.009	–0.008	–0.017	–0.009
np5t2	(0.012)	(0.003)	(0.004)	0.003	0.009	0.005
	–0.01	–0.01	–0.008	–0.007	–0.015	–0.009

Table A2: EASI Demand System; Linear 3 Stage Least Squares Estimation, Estimated from Equation (5). Selected Estimates from Equation (4) (Contd.)

VARIABLES	*Food*	*Housing*	*Heating*	*Pub. Tran*	*Priv. Tran*	*Education*
np5t3	(0.023)	(0.005)	0.007	(0.010)	0.005	0.027*
	–0.016	–0.011	–0.011	–0.011	–0.02	–0.014
np6t1	–0.050***	–0.050**	0.009	0.003	(0.001)	0.206***
	–0.017	–0.025	–0.006	–0.006	–0.009	–0.039
np6t2	(0.019)	–0.136***	(0.002)	0.000	0.005	0.122***
	–0.019	–0.023	–0.006	–0.006	–0.009	–0.034
np6t3	(0.032)	–0.085***	0.004	(0.004)	0.027*	0.125**
	–0.03	–0.03	–0.009	–0.01	–0.014	–0.053
Other controls						
Rural	0.006**	–0.027***	0.001**	–0.001	0.006***	–0.001
	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)	(0.004)
Dwelling built before 1960	0.026***	–0.078***	0.004***	–0.001*	–0.003***	0.026***
	(0.004)	(0.005)	(0.001)	(0.001)	(0.001)	(0.006)
Dwelling built between 1960-1980	0.028***	–0.093***	0.004***	–0.001	–0.002**	0.035***
	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)	(0.005)
Dwelling built between 1981-2000	0.022***	–0.070***	0.001	–0.001	–0.002**	0.027***
	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)	(0.005)
Quarter1	–0.002	0.008**	0.005***	0	0	–0.002
	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)	(0.004)
Quarter2	–0.001	0.006*	0.004***	–0.001*	–0.001	–0.011**
	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)	(0.004)
Quarter3	–0.003	0.006*	–0.002**	–0.001**	0	–0.002
	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)	(0.004)

Table A2: EASI Demand System; Linear 3 Stage Least Squares Estimation, Estimated from Equation (5). Selected Estimates from Equation (4) (Contd.)

VARIABLES	*Food*	*Housing*	*Heating*	*Pub. Tran*	*Priv. Tran*	*Education*
Central heating Gas	–0.008***	0.024***	–0.002***	0.001	–0.003***	–0.006
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.004)
Washing machine	–0.034***	–0.013	0.002	–0.005*	–0.003	–0.023
	(0.012)	(0.015)	(0.003)	(0.003)	(0.004)	(0.018)
Dishwasher	–0.008***	–0.001	0.002***	–0.001	0.001	–0.008**
	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)
Inverse Mills ratio	0.009	–0.004	0.001	0.007***	0.023***	–0.029**
	(0.010)	(0.012)	(0.002)	(0.002)	(0.003)	(0.015)
Constant	–0.048	–0.163	0.124***	0.007	–0.056	1.966***
	(0.134)	(0.165)	(0.031)	(0.031)	(0.047)	(0.200)
Observations	5,957.000	5,957.000	5,957.000	5,957.000	5,957.000	5,957.000
R-squared	0.513	0.346	0.576	0.264	0.411	0.565

Source: Author's analysis based on the Household Budget Survey. *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in brackets.

Table A3: Probit Estimation for the Sample Selection

Dependent children	0.103***
	(0.018)
County Borough	0.431***
	(0.024)
Suburbs or County Boroughs	0.369***
	(0.030)
Environs of County Boroughs	0.102***
	(0.029)
Towns 10,000+	0.056*
	(0.034)
Towns 5,001 - 10,000	0.130***
	(0.046)
Towns 1,000 - 5,000	–0.260***
	(0.058)
Mixed Urban/Rural Areas	–0.150***
	(0.040)
Rural Areas	–0.131***
	(0.032)
Garage in the dwelling	0.166***
	(0.018)
Constant	–0.748***

Source: Author's analysis based on the Household Budget Survey.
*$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in brackets.

Table A4: Uncompensated Elasticities

	Food	*Housing*	*Energy*	*Pub. transport*	*Priv. transport*	*Education*	*Services*
				First quartile			
Food	–0.87***	–0.009	0.011	–0.01**	–0.009	0.102***	0.02
	(0.024)	(0.015)	(0.006)	(0.004)	(0.008)	(0.015)	(0.014)
Housing	–0.052	–0.839***	–0.018**	–0.011**	–0.02**	–0.048**	0.092***
	(0.038)	(0.032)	(0.007)	(0.005)	(0.009)	(0.022)	(0.027)
Energy	0.233***	0.065***	–0.486***	–0.044***	0.041**	–0.01	0.042**
	(0.031)	(0.020)	(0.026)	(0.015)	(0.018)	(0.018)	(0.019)
Pub. transport	–0.14**	–0.064	–0.138***	–0.185***	–0.155***	–0.01	–0.105***
	(0.055)	(0.038)	(0.035)	(0.053)	(0.041)	(0.035)	(0.027)
Priv. transport	0.034	0.01	0.02	–0.053***	–0.507***	0.014	–0.007
	(0.038)	(0.024)	(0.016)	(0.016)	(0.034)	(0.020)	(0.020)
Education	0.14***	–0.047	–0.042***	–0.003	–0.018	–0.965***	0.047
	(0.052)	(0.034)	(0.010)	(0.006)	(0.012)	(0.034)	(0.047)
Services	–0.247***	–0.075***	–0.074***	–0.03***	–0.072***	–0.106***	–1.111***
	(0.040)	(0.027)	(0.008)	(0.003)	(0.009)	(0.023)	(0.040)
				Second quartile			
Food	–0.903***	–0.004	0.014***	–0.009***	0.001	0.074***	0.016
	(0.021)	(0.013)	(0.004)	(0.003)	(0.006)	(0.012)	(0.013)
Housing	0.032	–0.798***	–0.004	–0.011***	–0.002	–0.009	0.13***
	(0.028)	(0.025)	(0.005)	(0.004)	(0.006)	(0.019)	(0.023)
Energy	0.24***	0.058***	–0.472***	–0.059***	0.03	–0.036**	0.036
	(0.026)	(0.017)	(0.023)	(0.015)	(0.016)	(0.016)	(0.018)
Pub. transport	–0.125***	–0.12***	–0.149***	–0.115**	–0.206***	–0.003	–0.096***
	(0.047)	(0.032)	(0.031)	(0.046)	(0.035)	(0.031)	(0.027)
Priv. transport	0.067**	0.012	0.009	–0.07***	–0.569***	–0.015	0.007
	(0.030)	(0.018)	(0.012)	(0.013)	(0.025)	(0.017)	(0.019)

Table A4: Uncompensated Elasticities (Contd.)

	Food	*Housing*	*Energy*	*Pub. transport*	*Priv. transport*	*Education*	*Services*
Education	–0.041	–0.121***	–0.055***	–0.011***	–0.047***	–1.087***	–0.014
	(0.029)	(0.020)	(0.005)	(0.004)	(0.007)	(0.023)	(0.030)
Services	–0.113***	–0.033**	–0.04***	–0.016***	–0.038***	0.003	–1.076***
	(0.022)	(0.016)	(0.004)	(0.002)	(0.005)	(0.017)	(0.025)
			Third quartile				
Food	–0.936***	–0.012	0.015***	–0.009**	0.005	0.067***	0.006
	(0.022)	(0.015)	(0.004)	(0.004)	(0.006)	(0.015)	(0.014)
Housing	0.06**	–0.772***	0.004	–0.014***	0.005	0.04	0.151***
	(0.026)	(0.025)	(0.004)	(0.004)	(0.005)	(0.022)	(0.022)
Energy	0.253***	0.066***	–0.491***	–0.065***	0.013	–0.038	0.036
	(0.030)	(0.018)	(0.028)	(0.018)	(0.019)	(0.021)	(0.019)
Pub. transport	–0.117***	–0.177***	–0.139***	–0.143***	–0.229***	0.008	–0.092***
	(0.044)	(0.036)	(0.031)	(0.042)	(0.035)	(0.034)	(0.028)
Priv. transport	0.095***	0.012	–0.001	–0.091***	–0.574***	–0.029	0.015
	(0.033)	(0.019)	(0.014)	(0.015)	(0.026)	(0.021)	(0.023)
Education	–0.052**	–0.108***	–0.045***	–0.009***	–0.043***	–1.185***	0.018
	(0.024)	(0.019)	(0.004)	(0.003)	(0.005)	(0.026)	(0.027)
Services	–0.074***	–0.032**	–0.028***	–0.011***	–0.025***	0.055***	–1.088***
	(0.017)	(0.012)	(0.003)	(0.001)	(0.004)	(0.015)	(0.022)
			Fourth quartile				
Food	–1.23***	–0.108***	0.014	–0.018**	–0.006	0.294***	–0.089***
	(0.045)	(0.033)	(0.012)	(0.008)	(0.013)	(0.040)	(0.029)
Housing	0.003	–0.653***	0.02**	–0.036***	0.01	0.366***	0.34***
	(0.043)	(0.062)	(0.009)	(0.008)	(0.013)	(0.071)	(0.060)

Table A4: Uncompensated Elasticities (Contd.)

	Food	*Housing*	*Energy*	*Pub. transport*	*Priv. transport*	*Education*	*Services*
Energy	0.22**	0.072	–0.861***	–0.082	–0.083	0.278***	0.063
	(0.094)	(0.052)	(0.090)	(0.049)	(0.066)	(0.071)	(0.048)
Pub. transport	–0.271**	–0.463***	–0.15	–0.075	–0.383***	0.172	–0.196***
	(0.117)	(0.080)	(0.080)	(0.112)	(0.093)	(0.101)	(0.072)
Priv. transport	–0.002	–0.048	–0.066	–0.156***	–0.791***	0.178***	–0.014
	(0.076)	(0.051)	(0.046)	(0.039)	(0.074)	(0.065)	(0.057)
Education	0.151***	0.013	0.005	0.009***	0.012**	–1.52***	0.361***
	(0.018)	(0.016)	(0.004)	(0.003)	(0.005)	(0.034)	(0.035)
Services	–0.043***	–0.042***	–0.011***	–0.004***	–0.009***	0.195***	–1.325***
	(0.011)	(0.010)	(0.002)	(0.001)	(0.002)	(0.029)	(0.030)

Source: Author's analysis based on the Household Budget Survey. $*p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$. Standard errors in brackets.

Table A5: Mean Pollution Cost Provided by van Essen (2019)

		Air pollution	*GHG*	*Well-to-tank costs – Road*
		(*€-cent per vehicle km*)		
Petrol	Fuel efficient car: 99 g/km	0.16	1.41	0.53
	Fuel inefficient car: 180 g/km	0.16	2.56	0.96
	Fuel efficient car: 161 g/km	0.23	1.76	0.66
	Fuel inefficient car: 233 g/km	0.23	2.43	0.92
Diesel	Fuel efficient car: 89 g/km	0.95	1.26	0.29
	Fuel inefficient car: 119 g/km	0.95	1.69	0.39
	Fuel efficient car: 135 g/km	2.13	1.47	0.34
	Fuel inefficient car: 176 g/km	2.13	1.92	0.45

Source: van Essen (2019).

Table A6: Summary Statistics: Public Transportation Plus Communications

	Mean	*Std. Dev*
Budget shares:		
s1	0.235	0.116
s2	0.152	0.127
s3	0.047	0.034
s4	0.038	0.027
s5	0.053	0.037
s6	0.170	0.177
s7	0.304	0.172
Prices (logs):		
p1	4.236	0.255
p2	3.308	0.474
p3	3.780	0.382
p4	4.173	0.308
p5	3.978	0.340
p6	3.547	0.876
p7	2.676	0.952
Total expenditure	1,100.056	1,260.489
Other controls:		
Rural	0.382	0.486
Dwelling built before 1960	0.235	0.424
Dwelling built between 1960-1980	0.262	0.440
Dwelling built between 1981-2000	0.318	0.466
Central heating Gas	0.243	0.429
Washing machine	0.256	0.437
Dishwasher	0.258	0.438
N		16,152

Source: Author's analysis based on the Household Budget Survey.