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ECONOMIC AND TECHNICAL ANALYSIS OF ROAD TRANSPORT EMISSIONS

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Dissertation presented in partial fulfilment of the requirements for the degree of Doctor of Engineering

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Acknowledgements

The genesis of a dissertation can be considered as an adventurous trip through Ph.D. country. At the start of the journey you are looking forward to the new destinations that you will discover and the many interesting persons you will meet while roaming the country. Once on the road you recognise that the journey is full of surprises and you start to develop the art of travelling. And when the end of a successful journey nears and the final destination looms you feel satisfied when looking back on an enriching experience but at the same time a bit sad to finish such a great time.

As with all journeys, many hands help to make light work—that is especially true if the trip is a long one. For me it all started in 2000 when Ben Immers asked me to join the Traffic & Infrastructure group. Ben perfectly knew how to lure me into academics by offering me a position on a public transport related EU research project. That was the bait that drew me in. While working with Ben I got inspired by his endless creativity and I learned from him that there is no one single way to approach any topic in the multi-disciplinary science that is transportation research.

About one year later I was contacted by Stef Proost who was hiring for a position in transport economics modelling research. The topic was new to me, and I decided that it made sense to extend my horizon. Stef made sure that I read the right papers and guided me in developing and refining my intuition in economics over the years. It was a unique experience to be involved in state-of-the-art transport policy research as a member of the Energy, Transport & Environment group (ETE).

Both of my supervisors patiently reviewed many iterations of this final document. I am very grateful to them for their dedication, for the direction they provided in conducting the research and for the many improvements they suggested.

Also, I would like to thank the members of the supervisory committee as well as the examination committee for the many suggestions and comments I received from them after presenting my work.

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While working on all the projects I enjoyed the support of many colleagues. They are too many to name, but I want to thank all members of Traffic & Transport, ETE as well as the Spatial Economics department of the Vrije Universiteit where I finished this journey. I would also like to thank all the project colleagues working at the many other departments as well as the external companies who helped to make possible so many successful research projects.

Last but not least my exceptional gratitude goes to my family who have been supporting me throughout the long journey that brought me where I am now. For them it has been a very long trip indeed.

Samenvatting

Wegvervoer is een hoeksteen van het economisch systeem. De bijdrage die het levert aan het functioneren van de economie, en de daarmee verbonden maatschappelijke welvaart, is onbetwist. Door het wegvervoer veroorzaakte uitstoot brengt echter ongewenste schade toe aan de leefomgeving. Het beheersen van deze negatieve gevolgen is een integraal onderdeel van verkeersbeleid.

Uit het verlangen om tot een effectief en efficiënt uitstootbeleid te komen ontstaat de vraag naar modellen die aangeven wat de impact op uitstoot en maatschappelijke kost is van technologische en andere maatregelen. Dergelijke modellen identificeren de belangrijkste met wegvervoer verbonden gedragsdimensies, en waarderen de ermee verbonden impact op maatschappij en leefomgeving.

Het gepresenteerde onderzoek vertrekt uit bestaande modellen en geeft aan hoe deze uitgebreid worden om uitstoot van het gebruik van nieuwe voertuigtechnologieën te bestuderen. Vervolgens simuleren en analyseren we een reeks vervoersscenario's.

Met behulp van discrete keuzetheorie bestuderen we de voorkeuren van autokopers voor nieuwe voertuigtechnologieën op basis van een *stated preference* experiment. De analyse omvat een groot aantal gedragsvariabelen en technologieën en gebruikt daarvoor diverse gemengde logit specificaties.

Vervolgens geven we aan hoe de geïdentificeerde keuzepatronen kunnen vertaald worden naar een genest logitmodel dat kan gebruikt worden voor simulatie van maatregelen.

Bij het simuleren van scenario's voor autovervoer maken we een onderscheid tussen klimaatverandering en impact op de leefomgeving. Klimaatverandering is nauw verbonden met brandstofefficiëntie (en CO_2 uitstoot) terwijl de impact op leefomgeving afhangt van de totale uitstoot. Deze uitstoot is sterk afhankelijk van de gebruikte voertuigtechnologie. Als referentie voor een maatschappelijk verkiesbaar scenario maken we hierbij gebruik van beprijzingsscenario's.

Aansluitend simuleren we de bijdrage van openbaar busvervoer tot vermindering van impact op de stedelijke leefomgeving. De beschouwde beleidsvariabelen worden daartoe uitgebreid met het OV-aanbod. We bestuderen

tevens hoe oudere voertuigen kunnen aangepast worden met het oog op afname van uitstoot.

De belangrijkste inzichten van het onderzoek duiden het verband tussen bestaande of vernieuwende beleidsinitiatieven voor afname van uitstoot en de vraag naar vervoersactiviteit en de daarmee gepaard gaande impact op leefomgeving en welvaart.

Summary

Road transport is a key component of the economic system. Its contribution to the well functioning of the economy and the corresponding welfare of society is beyond doubt. There is however a negative side effect when emissions damage the environment. Controlling for this impact is an integral part of transport policy.

In establishing efficient and effective damage control policies the need arises for modelling tools to assess the impact of technological and other measures on emissions as well as social welfare. Such models represent the key behavioural dimensions that affect road transport emissions and value their impact on both society and the environment.

In our study we start from existing modelling tools and extend them for the assessment of emission damage reduction by new vehicle technologies. In a next step a number of transport scenarios are simulated and the results are analysed.

Using discrete choice theory for the analysis of a stated preference experiment we identify car buyers' preferences for new fuels and vehicle technologies. The scope of the analysis covers a wide range of behavioural variables and technologies, which are identified using panel based mixed logit model specifications.

In bringing the results of the analysis to the setting of a simulation model, it is shown how a nested logit model can be used to reproduce correlation patterns identified in the mixed logit analysis of the survey data set, the latter accounting for repeated choice.

In the simulations of private car transport scenarios a distinction is made between climate change and environmental damage. Climate change is closely related to fuel efficiency (and corresponding CO_2 emissions), whereas other environmental impact depends on the full range of emissions which vary over existing and new technologies. In both cases pricing scenarios play an important role as a reference for a socially desirable setting.

A further series of simulations focus on contributions to environmental damage reduction from bus public transport. Here we extend the range of policy variables considered to include level of service provision, and we also look to upgrading older vehicles.

Key insights of our study relate to how existing and novel policy approaches to emission reduction interact with transport activity and the related impact on the environment and global welfare.

Contents

Introduction

Motivation

Road transport is a key component of the economic system. Its contribution to the well functioning of the economy and the corresponding welfare of society is beyond doubt and widely recognised by policy makers.

Transport activity does however come at a price for society. Besides the obvious time and resource costs that go with its consumption, there have been identified a series of hidden costs for society, such as safety and environmental damage.

The need to account for the negative side effects of road transport has been recognised by policy makers in the implementation of transport policy plans. EU Commission established energy efficiency (and corresponding CO_2 emissions) as an important focus of its 2001 White Paper on transport policy (Commission of the European Communities, 2001). Similar concern on fuel efficiency has been observed by American and Japanese authorities (Plotkin, 2001).

In the 2007 Green Paper on urban mobility (Commission of the European Communities, 2007), the Commission reconfirmed its dedication to an integrated transport policy aiming at an effective transport system while mitigating its environmental effects through emissions.

A simplistic solution would be to order the reduction in the mobility of persons and goods or impose a redistribution between modes in order to contain its environmental impact. But the Commission recognises the constraint that such a policy approach would put on economic development. Moreover, the Commission has the power nor the means to impose such a measure.

Optimising the welfare contribution that road transport can make obviously calls for measures that enhance its efficiency with respect to environmental impact. Technological innovation and differentiated pricing are two measures receiving much attention in academic literature as well as in many existing policy plans including the White and Green papers mentioned above.

Technological innovation has proved its effectiveness as an environmental policy measure. The EU Commission recognises in its 2006 review of the

White Paper (Commission of the European Communities, 2006) the contribution made by technological innovation in order to meet tightened emission standards for road vehicles. Over the last 15 years, cleaner vehicles and fuels allowed to reduce overall transport NO_X and PM emissions in the EU by between 30 and 40%, despite the rising traffic volume.

Environmentally differentiated charges as a transport policy measure has however been much of an academic exercise for a long time. Only more recently have there been real world implementations such as the German LKW Maut.

In a subsequent section we will define the scope of our study of technological contributions towards a reduction in the environmental footprint of transport activity.

Scope of the study

In this study we analyse effects and social costs of using technological innovations and supporting policy measures to reduce emissions from road transport activity. For our analysis we design the appropriate modelling tools to simulate a range of relevant transport scenarios.

The main sources of *emissions* from road vehicles are exhaust gases and hydrocarbons produced by evaporation of the fuel (Hickman, Hassel, Joumard, Samaras, and Sorensen, 1999). A small amount of particulate matter emissions is caused by wear and tear (brakes and tubes), a source that we will leave out of consideration in our analysis.

An important determinant of the amount and composition of road transport emissions are the vehicle *technology* and fuel specification. Whereas some exhaust emissions are a direct result of the process of energy conversion and are hence closely correlated to fuel consumption (or energy efficiency), other emissions are a by-product of the thermodynamic cycle of the engine. Evaporative emissions are determined by fuel specifications and mainly originate from gasoline.

Although the production and distribution of fuels and vehicles involves the release of emissions as well, we will not study them provided that their abatement involves a technological and policy approach that is beyond our scope. An exception will however be made for electrical vehicles where the thermodynamic energy conversion is done at a fixed power plant, for reasons of comparability we will in this case include electricity production emissions.

In order to reach set emission targets, a government can decide for a range of *policy measures* that support the adoption and use of specific vehicle technologies. Traditionally there has been much inclination towards the use of technological standards which are imposed on new road vehicle sales. The Euro 1 through 5 standards are examples of how the EU authorities imposed emission limits on new road vehicles. Recently there has been more attention for using environmentally differentiated road pricing to realise emission targets. An example of such a policy is the German LKW Maut charge for heavy duty vehicles. In our study we will limit to policies which focus on the adoption and use of technologies in a larger area (such as a large city, region or country). Alternative emission policies could focus on local air pollution control and consider other policy instruments such as traffic management.

The scope of our study is limited to assessing the impact of measures that focus on reducing transport emissions through a change in the characteristics of vehicle technologies and transport modes such as price, fuel efficiency and technology availability. We do not explicitly model how technological innovation happens, it is rather assumed to happen externally to our study in which we assess its impact on vehicle technology use and emissions.

We furthermore explicitly leave out measures that aim at changing the taste of transport users through a marketing based approach. Also do we assume the user to be fully informed on all transport characteristics that he or she considers in any relevant decision. Finally we exclude from our analysis issues related to acceptability or the impact of policy makers and interest groups on the final implementation of a technological or policy measure.

Measuring the *effectiveness* of a measure or technology simply boils down to assessing its impact on aggregate emissions in the area considered. Total transport emissions can be expressed as a function of vehicle use and technology specific emission factors. The impact of new technologies or policy measures can be assessed by measuring the change in this indicator compared to a reference scenario. We will refer to this reference scenario as the *baseline*, which should ideally correspond to a business as usual scenario. The result of the effectiveness assessment can be used to test if an emission policy target is realised by a specific technology or policy measure.

Where we want to compare two measures with similar effectiveness, we need a more refined indicator. It is here that we introduce *efficiency*, which expresses how effectiveness compares to social costs. We define social cost of a scenario as the sum of all monetary and non-monetary costs incurred by different actors of a (geographically delimited) society. In the setting of our analysis, it mainly consists of four components: costs incurred by passenger transport users, costs for freight transport, changes in tax revenues and changes in social costs related to environmental impact of emissions. All cost components are expressed relative to a reference scenario. User costs are expressed as generalised costs which include both monetary and non-monetary costs.

For the effectiveness of a technology or policy measure there is an obvious scale to express their performance in reducing emissions. The baseline emission level corresponds to zero emission reduction, whereas the maximum possible reduction is the baseline emissions level itself. In order to define a similar scale for efficiency, we need for a definition of a scenario that corresponds to maximum social gains. Such a scenario is identified as *first-best*, and we will show in the subsequent section on the theoretical framework that it corresponds to a taxation policy where marginal user prices are set equal to marginal social costs. For this reason we will extensively use taxation scenarios in our efficiency assessment in order to set a benchmark for alternative scenarios.

In the next paragraph we will introduce the theoretical frameworks on which we draw in our study of the subject.

Theoretical framework

In this section we present the larger theoretical framework used in our study of the impact that technological innovations have on transport emissions.

The scope of the transport scenarios as outlined in the previous section calls for the identification of the factors determining the impact on emissions and social costs related to technological innovations and supporting policy measures. The impact of such scenarios on emissions is through a change in vehicle use. Vehicle technologies need to be classified according to their emissions profile (captured by emission factors) and the impact of the measure under consideration on activity of each class needs to be assessed using a simulation model. A secondary effect on emissions may occur when a change in transport activity affects the technology specific emission factors through traffic conditions.

In the short term the vehicle stock composition can be regarded as fixed an the only impact on vehicle use can happen through an increase or decrease of demand for transport activity. A change in transport demand incurred by technical or non-technical measures has a direct impact on the corresponding emissions and social costs. The change can be further detailed as an overall increase or decrease of demand for transport activity or a shift between different transport markets (e.g. transport modes). An indirect impact on transport emissions may happen through a change in traffic conditions where travel time (and speed) is impacted by demand levels in the corresponding transport infrastructure network.

In the longer term a change in transport activity demand may be accompanied by a change in vehicle stock composition. Both the size of the stock and the technological composition may be impacted in the transport scenarios we study. The size of the stock is dimensioned in order to meet transport activity demand levels, and hence its evolution is a direct function of the demand factors described above. The shares of the different emission technologies in the vehicle stock is the result of a more complex process where vehicles enter the stock upon purchase and stay in the stock over a longer period (unless a considerable decrease in activity demand or a technological measure would make part of the existing stock obsolete). A change in external conditions will primarily impact the purchase decision and be reflected in the vehicle stock composition only in the medium to longer term.

The output of different simulation components needs to be translated in effectiveness and efficiency of the measure in consideration. In the subsequent sections we will introduce the theoretical backgrounds of social costs after having discussed the technology emissions, transport demand and vehicle stock composition modelling frameworks.

Emissions and technologies

Emission factors express the amount of emissions that originate from vehicle technology use. A wide range of factors are available from literature, depending on the type of emissions, the component, the spatial and temporal resolution etc. For our study the factors should represent a rather high temporal and spatial resolution while at the same time provide sufficient detail with respect to the technological classification.

An appropriate emission methodology for our study is presented by Ntziachristos and Samaras (2000). The COPERT III methodology specifies factors that represent average real world emissions and fuel consumption for a wide range of conventional road vehicle technologies, engine sizes and fuels. The factors are based on a set of real world emission measurements and cover both hot engine and cold start emissions as well as gasoline evaporative emissions (mainly volatile organic components). The factors are function of environmental variables (such as ambient temperature), average trip length (to account for the share of cold start emissions) and average road network speed. Emission factors are calculated separately for three road types: urban, rural and motorways.

The classification of vehicle technologies closely follows legislative standards. Fuel efficiency however is not regulated and its evolution follows an autonomous trend.[1] This is not reflected by COPERT III for technologies beyond Euro 1. Indicators for the evolution of fuel efficiency do however exist in the form of test cycle measurement time series. Rather than legislation it is the vintage year that determines fuel efficiency. Emissions that are correlated to fuel consumption (such as CO_2 and SO_2) follow the same evolution. The emissions of sulphur are further determined by the sulphur content of the fuel, which is in turn determined by legislation.

As for alternative (or future) technologies, the same level of detail is typically not available although studies (such as Hickman et al., 1999) do

[1] This is in part caused by the agreements made between the EU Commission and the car manufacturers. But also in the period before there was an autonomous trend in fuel efficiency as reported by R. M. M. Van den Brink and Van Wee (2001). Small and Van Dender (2006) discuss the link between fuel prices and fuel efficiency. The topic of private car fuel efficiency is discussed in chapter 4.

provide factors which typically express emissions relative to a conventional technology, to allow for a consistent technology comparison.

The technological resolution of the emission factors determines the vehicle stock modelling approach described in the next paragraph.

Vehicle stock

Modelling the composition of the vehicle stock requires a methodology that describes how vehicle technologies enter and leave the stock in order to allow for the calculation of technological shares in vehicle use with sufficient detail for the emissions model at every moment of the modelling period.[2]

Our study focuses on how the technological composition of the vehicle is affected by technological and other measures. While there are measures such as scrapping schemes that stimulate the abandonment of (old) technologies, our focus will be on measures that impact the share of technologies that enter the vehicle stock.

Vehicles enter the stock when car drivers purchase a new vehicle. In such a situation, the car driver faces a discrete choice between a set of available technological alternatives. *Discrete choice theory* describes how the probabilities of each choice alternative are determined by an alternative specific utility representation. The utility U_i of each choice alternative i is the combination of a deterministic term V_i (function of observed variables) and a randomly distributed term ϵ_i (representing unobserved choice variables):

$$U_i = V_i + \epsilon_i \tag{1}$$

The car driver then chooses the alternative providing him or her with the highest utility U_i. An introduction on discrete choice theory is provided in appendix A.

To determine the scrapping of vehicles over a time interval a reference age distribution (based on historical data) can be applied. In a similar way one can account for the evolution in annual mileage over a vehicle life. In order to initialise the vehicle stock model a legacy stock needs to be provided for a base year.

The size of the stock is determined by the evolution in demand for transport activity which is discussed in the next section. The number of new vehicles over a time interval is then determined by the size of the existing stock together with the number of vehicles that leaves the stock over the period considered.

[2]We explicitly exclude the second hand market from our modelling scope as for our analysis the owner of the car is not important. There may however be second hand car trade between regions which influences the age distribution of the vehicle stock and the corresponding emissions profile. We will not consider this issue mainly because of a lack of data on the flow of second hand cars.

Transport activity

Levels of activity in transport markets are a key determinant of transport emissions through the size (and corresponding use) of the vehicle stock. Activity levels are determined by price levels on each market, whereas the prices itself are a function of production costs and taxes. The former relation is captured by the demand function, whereas the latter is described by the supply curve. Emerging prices and activity levels are determined by the intersection of both market specific curves.

Different transport markets can be distinguished based on place, time, trip motive, transport mode, etc. The subject of the study determines the appropriate level of detail in the representation of transport markets.

The concept of *generalised prices* is introduced here in order to have a single measure for all monetary and non-monetary costs related to the consumption of a unit of transport service. In the context of road transport activity (and under the assumption of perfect competition) it consists of three components: technology related resource costs (and taxes), fuel costs (and taxes) and time costs. To convert travel time to a monetary unit, value of time estimates are provided by past research (such as Jong and Tegge, 1998).

Supply functions are established by expressing generalised user prices as a function of transport activity level. The production cost levels in road transport are determined by technological design factors, such as capital and maintenance costs of the vehicle technology, fuel consumption, taxes, and road infrastructure travel time. The main impact of a change in activity level is through an increase in travel time costs, a relationship to be specified by a network specific aggregate congestion function. The congestion function also provides a representation of average speed, to be used as an input for the calculation of the technology specific emission factors discussed in the previous section.

Demand functions express how generalised user prices determine transport activity levels. The demand functions capture the road users' preferences with respect to distributing available income over different goods and services. The assumption is that the user optimises his or her utility for a given set of prices and under an income constraint.

A wide range of demand function specifications are discussed in literature. In our setting where we want to study how an average user changes his or her consumption of a service as a result of a change in generalised costs compared to a reference level, we use the constant elasticities of substitution (CES) specification presented by Keller (1976). The CES specification is an aggregate representation of discrete choice processes (consistent with utility maximising behaviour) and has the advantage of minimal calibration requirements: an externally provided reference (generalised) price and activity level for all transport markets together with substitution elasticities between markets allows to simulate the impact of changes in price levels.[3] For freight transport activity, a similar approach can be followed using a CES cost function.

Welfare

Different measures with an equal impact on transport emissions are equally effective but still can have a substantially different social impact. The concept of welfare is the appropriate measure to compare different policy instruments. For each scenario, we calculate the social costs related to the corresponding change in transport activity compared to a given reference level.

To compare the welfare impact of different transport scenarios in reducing emissions, we use the theoretical framework of the *partial equilibrium model*. The major assumption behind the approach is the absence of market distortions in (not modelled) non-transport sectors (or more exactly the measure does not impact the size of existing distortions in other markets), as well as the absence of income effects in the modelled transport sector.

Under these assumptions the normative indicator expressing welfare is a sum of components each representing a social cost related to the change in transport activity compared to a baseline level.

A first component is *consumer surplus,* which represents the loss or gain by users of passenger transport. We work with representative individuals so that we take an unweighted sum of costs over individuals. The cost concept for one individual corresponds to the compensating income variation: what change in income is needed to make the individual accept the new prices and quality offered to him in the new equilibrium. The CES demand specification allows for a straightforward calculation of this component.

A second component is *producer surplus* which is similarly calculated directly from the CES cost function for freight transport.

A third component is the impact of the scenario on *tax revenues*. The changes in taxes, subsidies and public transport profits are by assumption returned to the representative consumer. This change can be calculated directly from the transport activity modelling framework.

One needs further to account for the distortionary effect of raising taxes in other sectors. The concept of *marginal cost of public funds* (MCPF) accounts for this shadow cost (or gain) that corresponds to a change in tax revenue. In order to determine the size of the MCPF factor, one needs to specify the sector in which the compensating distortionary taxes are changed. In our study we will assume that a change in tax revenue from transport activity is compensated by a corresponding change in labour taxes.[4]

[3] The relation between the CES model and the logit model is discussed by Anderson, Palma, and Thisse (1992). For a discussion of the application in transport demand simulation we refer to De Palma, Proost, and Van der Loo (in press) or the TREMOVE model documentation (European Commission, Standard & Poor's DRI, and Katholieke Universiteit Leuven, 1999).

[4] We use the approach by Ochelen, Proost, and Van Dender (1998) who present a value of

A last welfare component are external social costs related to *emissions*. For each pollutant cost factors are provided by literature (for instance Friedrich and Bickel, 2001) that express in monetary units the external impact of a marginal increase of emissions.[5] These factors are based on atmospheric models that relate emissions to concentration levels, which are further linked to a number of impact conditions each of which are valued (i.e. expressed in monetary terms). The factors typically vary over urban and non-urban areas, the former factors being higher compared to the latter as a result of higher population densities. A notable exception to this is CO_2 which is not toxic and its only social impact is through global climate change.[6]

As has been discussed in the previous section, the scale for efficiency is set by the first best scenario for which welfare reaches a maximum level. Economic theory sets out that maximal welfare occurs at consumption levels that correspond to user prices that are equal to marginal social costs. This can be realised by setting taxes equal to the external costs, which in the framework of our study correspond to congestion and environmental impact.

Methodological Approach & Reading Guide

In our study of the cost benefit assessment of measures reducing road transport emissions, we apply a capita selecta approach. The study consists of two main parts: behavioural analysis and policy simulation.

The *first part* analyses car driver preferences for alternative fuels and vehicle technologies. This part extensively draws on discrete choice theory for the analysis of survey data and the design of a simulation tool.

1,2 for the marginal cost of public funds and a share of labour income in total income of 70%. The contribution of the MCPF component to welfare is then equal to 6,6% of the increase in tax income for the government. Other studies (for instance Kleven and Kreiner, 2003) present higher values for the marginal cost of public funds. In our simulations we will report the contribution of the MCPF cost component separately in order to provide an indication for the sensitivity of the net welfare result to the assumed allocation of the change in tax revenues and the valuation of the selected allocation. Note that these assumptions do not feed back in the model but affect the size of the MCPF social cost component only.

[5] In our simulations we use values for the marginal external emission cost coefficients from a draft version of TREMOVE 2 which are based mainly on Friedrich and Bickel (2001) and which are presented in appendix C. Other studies (for instance Maibach et al., 2008) as well as later versions of TREMOVE 2 (based on Holland, Pye, Watkiss, Droste-Franke, and Bickel, 2005) use values that are lower by a factor of up to three. In our simulations we will report the contribution of the external emission cost component separately in order to provide an indication for the sensitivity of the net welfare result to the valuation of external impact.

[6] As opposed to the other pollutants we use for CO_2 emissions an external cost factor that is based on a reference value of economy wide marginal abatement cost. The rationale is that total EU-wide CO_2 emissions are capped by the Kyoto agreements. An increase of CO_2 emissions in one sector needs hence to be compensated by a decrease elsewhere in the economy. The reference value we use for external abatement cost is provided by TREMOVE 2 and is based on Holland, Hunt, Hurley, Navrud, and Watkiss (2005). This value is of a similar order of magnitude as values provided in literature for marginal environmental impact by CO_2 emissions.

A first chapter discusses the design of a conjoint choice experiment and presents the corresponding findings on car purchase behaviour.

The second chapter presents an approach to use the survey data set for the design of a simulation tool for car technology procurement. It is illustrated how a *nested mixed logit* model specification allows to account for the repeated choice setting of the survey in order to identify correlated preferences for technologies. In a subsequent step a computationally efficient nested logit specification that replicates the correlation pattern is presented.

Finally the alternative technology model is integrated in the larger transport modelling framework of TREMOVE which is a proven model for evaluation of emission policies. This integrated model will be used for simulation of transport scenarios in the second part of the study.[7]

The *second part* of the study presents the assessment of the effectiveness and efficiency of a series of transport scenarios in which technological innovation is used to reduce road transport emissions. A first chapter studies the contribution to be expected from alternative private car technologies and fuels. A second chapter is dedicated to energy efficiency and the corresponding CO_2 emissions from traditional private car technologies. A last chapter studies contributions to emission reductions from public transport activity in urban areas.

For each simulation chapter a customised version of the TREMOVE model is implemented. The role of this simulation tool is to provide a consistent framework for the comparison of the effectiveness and efficiency of the different technical and non-technical measures.

The model simulations each focus on the impact of a small change in external variables on transport activity and emissions over the modelling period. These simulations allow us to study the impact of isolated policy measures.

The time period over which to change the course of external variables in a scenario is entirely arbitrary in a simulation exercise. In the context of this study we should however account for the lifetime of technologies in the vehicle stock. In order to allow for an understanding of long term impact, simulated measures should cover a sufficiently long time period. At the same time the end of the modelling period was fixed to 2020 to fit the availability of sufficiently detailed (and consistent) external baseline forecasts for model

[7]The methodological approach for the simulations is to use the framework of the TREMOVE model as a starting point and extend it. This approach allows for the use of an existing and proven modelling framework (including a consistent reference scenario) while focussing on behavioural extensions of it. A drawback is that each extension needs to be designed consistent with the larger modelling framework dictated by TREMOVE (an issue which is much the focus of the second chapter). An alternative bottom-up approach would be to design a partial equilibrium model tailored for (and entirely consistent with) the behavioural topic of the study. That would be an enormous exercise, and while allowing for more theoretical flexibility it would still be confined by limitations in data availability.

calibration.[8]

It is key to understand that the strength of the modelling approach is in the consistent comparison of individual measures. By no means is the model to be regarded as a forecast tool. To forecast developments in transport activity one has to consider a wide range of variables, whereas in TREMOVE a baseline evolution of activity and prices over the modelling period is taken as given in the model calibration, hence any forecasting is external to the model.

Furthermore, TREMOVE is not an optimisation tool. In a static context the welfare optimal price levels under a series of constraints is an illuminating exercise. But the time dynamic nature of the technology stock makes optimisation burdensome, and the results would be dependant on the applied discount rate. As noted by Arrow et al. (2004), the right value of the discount rate is a matter of much debate which we will not further consider here.

For clarity we want to draw the attention of the reader to the monetary unit used throughout all simulation exercises presented in this study. Unless mentioned differently, all costs and prices have been expressed in constant prices of the year 2000. For actualisation a social discount rate of 4% per year was used.[9]

The common base for the simulations in the second part is the TREMOVE model for Belgium. A hybrid version is used that draws mainly on version 1.3a with some relevant upgrades from version 2 included. A discussion of the base model including baseline and other assumptions is presented in appendix C.

In the first chapter of the second part the extended private car technology choice model developed in part one is added to the base model.

The second chapter uses a model where availability of private car technology is again limited to traditional diesel and gasoline technologies, but the model is now extended with an internal representation of fuel efficiency for all road transport vehicles.

The last chapter limits the model to the Brussels metropolitan area and uses an updated baseline for public transport modes. The model is here extended with an internal representation of optimal public transport user prices and service provision level.

[8]To provide an indication we mention here that in our simulation model the expected (technical) lifetime of a private car is 9,5 years (see appendix D). The modelling horizon sufficiently accommodates for the representation of the corresponding transient effects.

[9]Zhuang, Liang, Lin, and De Guzman (2007) provide an overview of the state of practise around the world in public discount rate policy. They draw the conclusion that developed countries apply rates of 3–7%. In our simulations we will report undiscounted costs for a selection of years over the modelling period, in order to provide an indication of the evolution of costs. The discount rate is applied where these yearly costs are aggregated in a single net present value indicator.

List of notations and acronyms

Notation

Model design and estimation

The notation used in discrete choice model design and estimation is applied in chapters 1 and 2 and appendixes A and C.

Notation	Meaning
j, k, m, n	indexes used to indicate alternative j, nest k, choice set or choice situation m and consumer or respondent n
U_{jmn}	random utility of choice alternative j as obtained by consumer n in choice situation m
V_{jmn}	deterministic part of U_{jmn}, function of x_{jmn}
α, β	vector of model coefficients
$\hat{\beta}$	estimate of β
x_{jmn}	vector of variables relating to consumer n and alternative j in choice situation m
z_{jmn}	vector of variables relating to consumer n and alternative j in choice situation m (used in mixed logit utility specification)
ϵ_{jmn}	stochastic part of U_{jmn}
μ_{jmn}	stochastic utility in a mixed logit model specification (expected value of μ_{jmn} is zero)
P_{jmn}	choice probability of alternative j chosen by consumer n in choice situation m
$E(\gamma)$	expected value of a stochastic variable γ
$\mathrm{Var}(\gamma)$	variance of a stochastic variable γ
η_{kmn}	stochastic utility in a nested logit model specification
σ	scale parameter of the Gumbel distribution
I_{kmn}	inclusive value of nest k
λ_k	inclusive value coefficient of nest k
p	p-value, indication of significance of a coefficient estimate

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Notation	Meaning
t	t-statistic, indication of confidence interval of a coefficient estimate
K	number of nests
N	sample size (=number of respondents)
M	number of choice sets per respondent
J	number of alternatives per choice set
B	amount the respondent indicated he or she would spend on a new car in case he or she had to buy one at the moment of the survey
δ	dummy variable, can have values 0 or 1 only
Δ	difference
r	ratio of variance of two stochastic terms, used to compare two model estimations
$f(\gamma)$	probability density function of a stochastic variable γ
$F(\gamma)$	cumulative distribution function of a stochastic variable γ
S_k	set of alternatives j that belong to nest k
a	scale factor, used to scale utility U_{jmn} of a model
s	scale factor, used to scale the estimation data set (x_{jmn})
d_n	expected annual mileage by respondent n
PC_{jmn}	value of the purchase cost variable for alternative j in choice set m faced by respondent n
AC_{jmn}	annual cost
FC_{jmn}	fuel cost
LFC_{jmn}	lifetime cost
i	discount rate used to amortise medium run capital investment
y	expected vehicle lifetime
$V_{c,p,r,t}$	speed in year t in period p on road type r for vehicle class c
$F_{p,r,t}$	flow (in passenger car units per hour) in period p on road type r
$A_{c,r,t}$	coefficient in congestion function
$B_{c,r,t}$	coefficient in congestion function
c	vehicle class: truck/bus or private car/motorcycle
r	road type: Brussels, other urban, motorway or other road
p	period: peak or off-peak

Policy simulation

The notation presented in the following table is applied in chapters 3, 4 and appendix D.

Notation	Meaning
f	fuel intensity in litre per kilometre
p	fuel price in euro per litre
ϵ	fuel price elasticity of fuel intensity
UC	user cost (including taxes) in euro per vehicle kilometre
RC	resource costs (including taxes on resource costs) in euro per vehicle kilometre
e	emission factor in gram per vehicle kilometre
E_{ap}	annual emissions of pollutant p at vehicle age a
C_p	marginal external emission cost coefficient for pollutant p in € per ton
C	constant
δ_j	dummy variable for technology j
β_{cat}	coefficient of choice model for technology class *cat*
LFC_j	lifetime user cost of technology j
y	expected vehicle lifetime
EC	expected emission cost over the entire expected vehicle lifetime
i	discount rate used to amortise medium run capital investment
Δ	difference
λ_k	inclusive value coefficient of nest k of a nested logit model specification
v	CO_2 emissions per fuel unit

The notation presented in the following table is applied in chapter 5.

Notation	Meaning
C_o	is the operating cost in euro per vehicle kilometre (vkm)
D	is the average occupancy rate (in travellers per vehicle)
V_w	is the value of time during waiting (in euro per hour)
f	is the average frequency (in departures per hour per direction)
L_t	is the average trip length (in pkm)
C_w	is the walking cost from/to the stop
V_t	is the in-vehicle value of time (in euro per hour)
C_e	is the marginal external emission cost (in euro per vkm)
T	is the commercial travel time (in hour per km)
q	is the level of demand (in pkm per hour)
L_n	is the network length (in km)
B	number of buses
S	no-travellers speed
δ	time (in hours) necessary to slow down, open and close the doors and to re-accelerate at a stop

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Notation	Meaning
ϵ	time (in hours) necessary to let a user embark/disembark
d	the average stop distance
a, b	COPERT III technology specific parameters

Acronyms

Acronym	Meaning
ACEA	Association des Constructeurs d'Automobiles
CAFE	Corporate Average Fuel Economy
CATI	computer assisted telephone interviewing
CES	constant elasticities of substitution
CNG	compressed natural gas
CH_4	methane
C_6H_6	benzene
CO	carbon monoxide
CO_2	carbon dioxide
EU	European Union
EV	electric vehicle
GDP	gross domestic product
H_2	hydrogen
HDV	heavy duty vehicle
HH	household
IG	integrated model
IIA	independence from irrelevant alternatives
iid	independent and identical distributed
ICE	internal combustion engine
JAMA	Japan Automobile Manufacturers Association
KAMA	Korea Automobile Manufacturers Association
LA	Los Angeles
LDV	light duty vehicle
LFC	lifetime cost
LL	log-likelihood
LPG	liquefied petroleum gas
MCPF	marginal cost of public funds

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Acronym	Meaning
MIE	main income earner
MIVB	Maatschappij voor het Intercommunaal Vervoer te Brussel
ML	mixed logit
MNL	multinomial logit
NG	natural gas
NL	nested multinomial logit
NMBS	Nationale Maatschappij der Belgische Spoorwegen
NMVOC	non methane volatile organic compounds
N_2O	laughing gas
NO_X	nitrogen oxides
NPV	net present value
pkm	passenger-kilometre
PM	particulate matter
RP	revealed preference
RUM	random utility maximisation
SP	stated preference
TEC	Transport En Commun
tkm	ton-kilometre
TWC	three way catalyst
UK	United Kingdom
VAT	value added tax
vkm	vehicle-kilometre
VOC	volatile organic compound
WTP	willingness to pay

CHAPTER 1

Modelling the choice for alternative cars

1.1. Introduction

The development of alternative car technologies has received much attention from both authorities and car manufacturers as a way to reduce emission levels and energy consumption of transport activity. Major research and development efforts result in a broad range of new fuels (e.g. hydrogen) and new private car technologies (e.g. hybrid cars) which all seem to have interesting characteristics when compared to the existing diesel and gasoline options.

There is however a difference between the technological and environmental specifications of the individual car and the overall environmental impact of transport activity. Before a new technology can contribute to air quality improvements, people need to actually buy it. In this chapter we concentrate on the choice of a new private car in Belgium.

Discrete choice theory (Anderson et al., 1992; Ben-Akiva and Lerman, 1985; K. Train, 1986/1990; K. E. Train, 2003) provides a powerful modelling framework to analyse choice behaviour of consumers, and has been widely applied in transportation research to study modal choice, destination choice, private car choice etc. With the advent of more powerful computers a shift is noticed from the multinomial and nested logit choice models to the mixed logit choice framework.

The analysis of technology choice behaviour in past research falls roughly apart in two categories, based on the approach applied in the collection of the choice data set used: stated preference or revealed preference.

Revealed preference research allows for a highly detailed choice data set including information on large numbers of car purchases and all choice alternatives that are available on the market. Some examples are COWI A/S (2002); De Jong (1996); Verboven (1996). Difficulties encountered by the revealed preference approach typically relate to correlation in choice variables and the technological scope of the choice data being limited to conventional technologies only (alternative technologies not being widely available on the market). The modelling specification applied in these papers is logit or nested logit, probably because of the computational demands caused by the large choice set dimensions. An exception is Brownstone, Bunch, and Train (2000) who apply a mixed logit specification in a joint stated and revealed preference estimation.

Stated preference research on technology choice has focused much on the choice for alternative fuels as well as battery cars. The stated preference approach allows to avoid correlation issues and allows for the inclusion of alternative technologies as well as variation in more exotic choice variables such as refuelling range. Some examples are Batley, Knight, and Toner (2003); Brownstone and Train (1999); Bunch, Bradley, Golob, Kitamura, and Occhiuzzo (1993); Ewing and Sarigöllü (1998); Ramjerdi and Rand (1999). The surveys focus on different geographical regions but with much similarity in the survey procedure which seams to be particularly robust. Early examples apply a nested logit setting in the choice analysis (revealing similar correlation patterns over different studies), whereas more recent research implements mixed logit model specification.

In our study of the topic we will apply the stated preference approach. We will use the survey procedure developed in past research as a base and update the design in order to allow for some extensions to past research.

In this chapter we will extend the technological scope[1] in order to include the choice for hybrid power-trains (hybrid cars seem not to be covered by most past research, Bunch et al. (1993) being an exception) as well as fuel cell powered technologies. The private car technologies we want to study in this chapter include both existing, conventional (diesel, gasoline, LPG) and new, alternative technologies (e.g. fuel cell powered, alternative fuels, hybrid power train equipped).

Another unexplored territory by past research is the geographical focus on Flanders[2] in our study. Most past research focused on car markets where only one technology (gasoline) was available for private cars at the moment of the survey. None of the studies mentioned did study differences in correlation between two or more established technologies (e.g. diesel and gasoline) at one hand and alternative technologies at the other hand. In contrast we will use the opportunity of having two established technologies (diesel and gasoline) on the Flemish market to study these correlation patterns.

Finally, most past studies did not cover all cost variables, in most cases

[1]The technological scope of our study is discussed in section 1.2.1.
[2]The Flemish Region is one of the three official regions of the Kingdom of Belgium.

excluding annual costs such as maintenance which may differ significantly between technologies (e.g. replacement of battery pack for the electric car).

In our application we refine the survey design and show how it can be successfully applied to a significantly smaller sample compared to past research on the topic.

In our analysis of the choice data we compare multinomial, nested and mixed logit specifications. The mixed logit specification provides the best results as it can accommodate for the repeated choice character of the data set. This finding is in line with past research by Batley et al. (2003). Analysis of the choice data reveal no significant preferences for hybrid technologies. Correlation patterns analysed reveal strong fuel-specific correlations in preferences for technologies.

The structure of the chapter is as follows. In a first section we define the scope of the research and provide a short introduction on discrete choice theory which is the modelling framework we use. A second section reviews the literature. The third section reports on the results of a focus group session. Two further sections focus on the design and implementation of the survey to collect stated preference data. The sixth section discusses the estimation of a model and the last section concludes the chapter.

In a subsequent chapter (chapter 2) we will use our analysis to design a simulation tool and show how we can integrate this alternative technology choice model in the partial equilibrium model TREMOVE. In chapter 3 we will then calibrate the model for Belgium and analyse the potential of alternative technologies to contribute to a reduction of external emission cost.

1.2. Scope and modelling framework

In this section we first discuss the scope of the choice analysed in this chapter. In a second subsection we introduce the modelling framework of discrete choice theory and in a last subsection we discuss the use of stated preference versus revealed preference data in model estimation.

1.2.1. Scope

A consumer who wants to buy a new car faces a rather extended choice set of cars that are available on the market. Different values for brand, car body, colour, comfort equipment, engine size etc. define the range of choice alternatives and the consumer has to make a decision on his preferred combination.

In this chapter we will limit our attention to the choice between *technologies*, both conventional and alternative. With *technology* we indicate the combination of fuel (including electricity), engine and power-train. This means that the choice we study is the one between different vehicles that are identical in all properties except for the driving technology.[3]

We will limit the geographical scope of our research to the preferences by Flemish consumers. Conventional technologies that are broadly available on the Flemish car market include gasoline, diesel and LPG fuelled internal combustion engines.

For alternative technologies, a broad range of fuel, engine and power-train combinations have been discussed in the past. Arcoumanis (2000) and International Energy Agency [IEA] (1999) focus on alternative fuels, whereas Burgwal, Dijkhuizen, Mourad, Smokers, and Winkel (2001) provide an overview of hybrid power-train technologies as well as electrical battery and fuel cell powered vehicles. Verbeiren, De Vlieger, Pelkmans, De Keyser, and Springael (2003) conduct a sustainability assessment of a varied range of conventional and alternative technologies.

To allow for the analysis of the potential of alternative technologies (which will be conducted in chapter 3) we need to define the technological scope accordingly. The scope should cover a range of (improved) conventional and innovative technologies that are sufficiently diverse in technical and economic characteristics and for which consistent data is available to allow for simulation. The selection by Verbeiren et al. (2003) meets this requirements, we decide to use it as definition of the scope of our study (see table 1.1).

We will limit the analysis in this chapter to the choice made by private consumers, and leave the technological preferences of business consumers beyond the scope of our research. Some earlier private car technology choice models include a separate sub-model for company and private car purchase (e.g. COWI A/S, 2002). There is however very limited knowledge on the size,

[3] In our study we assume that the choice between technologies is independent from brand, car body etc.

Table 1.1. Technological scope of the choice analysed (based on Verbeiren et al., 2003)

Technology
Gasoline
Gasoline hybrid
Diesel
Diesel hybrid
LPG
CNG
CNG hybrid
Hydrogen
Hydrogen hybrid
Hydrogen fuel cell
Battery electric

composition and specific dynamics of the company car stock for Flanders. Lacking insight in key aspects of the structure of this specific car market hampers the study of specialised issues such as preferences for alternative vehicle technologies.[4]

1.2.2. Discrete choice theory

Discrete choice theory provides a broad range of modelling frameworks. An extended introduction on the topic is provided in appendix A. An in depth discussion on discrete choice theory can be found in Anderson et al. (1992); Ben-Akiva and Lerman (1985); K. Train (1986/1990); K. E. Train (2003).

The consumer who considers the purchase of a car faces a discrete choice problem. Discrete choice theory models the probability that a consumer n chooses a given alternative j in choice situation[5] m as a function of the *random*[6] *utility* U_{jmn} of the alternatives, expressed as:

$$U_{jmn} = V_{jmn} + \epsilon_{jmn} \tag{1.1}$$

where:

- V_{jmn}: the *deterministic part* of the utility for alternative j as obtained by consumer n in choice situation m—we will in this section assume that V_{jmn} is linear in parameters: $V_{jmn} = \beta' x_{jmn}$ with β a vector of coefficients and x_{jmn} a vector of decision variables relating to consumer n and alternative j in choice situation m;
- ϵ_{jmn}: the *stochastic part*.

The consumer then chooses the alternative with the highest utility (utility maximisation).

The *multinomial logit* model (MNL) assumes a Gumbel distribution with variance of the stochastic utility $\mathrm{Var}(\epsilon_{jmn}) = \sigma^2\pi^2/6$.[7] This assumption results in a closed form for the choice probability of alternative j chosen by consumer n in choice situation m:

$$P_{jmn} = \frac{e^{\beta' x_{jmn}/\sigma}}{\sum_i e^{\beta' x_{imn}/\sigma}} \tag{1.2}$$

As we can see from expression (1.2), any linear transformation of x_{jmn} does not affect the choice probabilities. This makes it impossible to identify

[4] Wuyts (2009) has conducted a survey of company car use in Flanders. His focus was mainly on issues related to labour economics, which fall well beyond the scope of our study.

[5] The index for choice situation m is introduced here to allow for the repeated choice character of survey data.

[6] Where we discuss or apply discrete choice theory we will use the terminology that is common in the literature (for instance K. E. Train, 2003). *Random* utility could be understood as being *probabilistic* in character.

[7] Note that throughout this and the subsequent chapter σ denotes the scale parameter of the Gumbel distribution and not the variance which is noted as $\mathrm{Var}(\epsilon)$. A full overview of notations and acronyms is provided in the introducing sections.

the value of the scale parameter σ of the stochastic part separately from the true coefficients β of the deterministic part. In estimation the utility U_{jmn} is scaled by a factor $1/\sigma$ which normalises the variance of the stochastic part to $\pi^2/6$. The estimated coefficients $\hat{\beta}$ include the scale parameter σ of the stochastic utility:

$$\hat{\beta} = \beta/\sigma \tag{1.3}$$

Appendix A discusses how the scale parameter of two independent model estimations can be compared using the ratio of their respective coefficient estimates $\hat{\beta}$.

The *nested multinomial logit* model (NL) extends the MNL specification by allowing for correlation in unobserved preferences (stochastic utility) for a subset of alternatives. A partition structure defined by the researcher groups the alternatives in subdivisions or nests. The more substitutable alternatives are grouped in lower nests in the tree structure. For each nest k the coefficient λ_k ($0 \leq \lambda_k \leq 1$) is a measure for the correlation between the alternatives in nest k, with values closer to unity indicating less correlation.

The *mixed logit* model (ML) is a further extension to the multinomial logit specification that provides a very flexible modelling framework. It defines the utility U_{jmn} as:

$$U_{jmn} = \alpha' x_{jmn} + \underbrace{{\mu_{jmn}}' z_{jmn} + \epsilon_{jmn}}_{\text{stochastic utility}} \tag{1.4}$$

with

- α a vector of fixed coefficients
- μ_{jmn} a vector of random terms with mean zero and probability distribution $f(\mu_{jmn})$, any distribution can be used (independence over j, m or n is *not* a necessary condition)
- x_{jmn} and z_{jmn} vectors of observed variables
- ϵ_{jmn} i.i.d. Gumbel distributed with scale parameter σ normalised to unity (independent over all alternatives j, choice situations m and respondents n)

In order to better understand the potential of the mixed logit specification to account for a repeated choice situation, we rewrite the utility formula (1.4) as:

$$U_{jmn} = \alpha' x_{jmn} + {\mu_n}' z_{jmn} + \epsilon_{jmn} \tag{1.5}$$

with μ_n a vector of random terms with mean zero which are independent for all respondents n (but constant over choice sets m).

The error terms μ_n introduce correlation between the utility U_{jmn} of alternatives j of the different choice sets m faced by the same respondent. The vector z_{jmn} may or may not include the same variables as x_{jmn}, this depends on the correlation pattern studied.[8]

[8]Based on the discussion of the mixed logit specification by Batley et al. (2003).

1.2.3. Stated preference and revealed preference

To analyse the choice behaviour of consumers, we need an observation data set. Roughly two approaches exist for the collection of the data set for the analysis of technology choice: revealed preference and stated preference.

The *revealed preference* approach uses observations of actual choices made by consumers. This approach has the major advantage that there is no doubt that the data set reflects real world behaviour.[9] But it may be difficult to use these data for model estimation. Brownstone et al. (2000) indicate that a major difficulty in estimating revealed preference car choice models is the correlation in decision variables. A second problem that arises is the correct definition of the choice made: both the choice set and the choice variables have to be defined by the researcher. Finally, studying preferences for new car technologies may necessitate to assess the effect of values of characteristics that are beyond the range observed in the revealed data sample.

The *stated preference* approach overcomes these difficulties by using a custom designed survey to collect the choice observations. This provides the researcher with much control over the choice sets faced by each respondent: both the number of alternatives, the variables in which they differ and the levels of these variables are controlled in the survey setup. This allows to eliminate correlation in choice variables as well as to eliminate the influence of non-observed choice alternatives or variables. The major disadvantage of the stated preference approach is that what is measured are the intentions of the consumer, without any guarantee that they correspond to real world behaviour. This may be a specific concern when the levels of presented decision variables are well outside the range experienced by the respondent in real world behaviour.

Research focusing on the choice between conventional technologies has made use of revealed preference data (some examples are De Jong, 1996; Verboven, 1996). However, Bunch et al. (1993) argue that the current limited supply of alternative private car technologies excludes the revealed preference approach for the analysis of the choice for alternative technologies.

In this chapter we will follow the approach by Bunch et al. (1993) and conduct a survey in order to collect a stated preference data set that allows for the analysis of the choice for alternative technologies. Before we design the survey, a focus group is conducted in order to gain a better qualitative understanding of the choice process. An overview of existing experience on the stated preference approach in the analysis of alternative car technology choice allows us to optimise the survey design.

In a subsequent chapter (chapter 2) we will compare our stated preference approach to an existing revealed preference choice model for conventional technologies and discuss how both models can be integrated in order to

[9] Assuming no measurement bias.

combine advantages of both approaches.

1.3. Literature review

Different choice models have been developed in past research for the analysis of choice behaviour for new electric and alternative fuel technologies. Since these technologies are not available on the market in large quantities, these models have been estimated making use of *stated preference data* (SP) collected through a survey. Several modelling frameworks have been applied, we will limit the review to multinomial logit, nested multinomial logit and mixed logit choice model specifications.

The focus of our review will be on:

- *technology attributes* that have been proved to be significant in the choice process;
- *survey design*: sample size, response rate, survey setup with special focus on the choice set design (e.g. number of alternatives per choice set).

Throughout this chapter we will use the p-value as a measure of coefficient significance in the different models discussed. The p-value of a coefficient estimation $\hat{\beta}$ indicates the probability that, given that the null hypothesis (true coefficients are zero) is true, the coefficients β assume a more extreme value than the observed (estimated) $\hat{\beta}$. As a rule to decide on significance, we will use in this chapter $p \leq 0{,}05$. Although any threshold value for significance is entirely arbitrary, insights gained in simulations we conducted (see section 1.5.7) resulted in the specified level.

The p-values reported in this literature review section have been added by ourselves based on standard errors or t-statistics reported in literature (as far as the p-values have not been provided in the original text). This common measure of coefficient significance simplifies the comparison of the different models discussed here.

1.3.1. California

Much research on private car technology choice has been conducted in California for the development of a micro-simulation model of the vehicle market in the greater LA area.

Bunch et al. (1993) conducted a pilot study and estimated a nested multinomial logit (NL) model based on stated preference (SP) data. They conducted a survey in three phases, resulting in 562 returned questionnaires (20% response rate). Three model specifications are estimated. The first model (table 1.2) only includes technology-specific variables, whereas subsequent models extend the specification by including interaction variables. Five technology types were included in the model: gasoline, alternative fuel only, multiple-fuel (alternative fuel and gasoline), electric and hybrid. Hybrid car technology was here described as a car that is able to run on gasoline and/or electricity.

The survey used a three phase setup, where in a first phase background information on the respondent was collected, in the second phase the respondent made a choice between alternative technologies and a third phase focused on the choice between fuels (for multi-fuel vehicles). The car technology choice sets included 3 alternatives, each alternative was presented with six or seven variables. The net sample size that finished the second phase was $N = 692$,[10] where each respondent completed five choice sets. The response rates were 40% for phase 1 and 26% for phase two.

Some coefficients in the model were found not to differ significantly from zero ($p \leq 0{,}05$): alternative fuel, electric vehicle and the possibility to charge at work as well as at home for electric vehicles. Also the constant for hybrid electric is not significant.

The log-sum coefficient representing correlation in preference for non-electric vehicles differs significantly from zero.

Further Californian research on the topic includes Brownstone, Bunch, Golob, and Ren (1996) who built a large multinomial logit (MNL) model based on new SP data. The same data have been reused by Brownstone and Train (1999) to compare MNL with mixed logit (ML) models (table 1.3). In the survey, four technology types were included: gasoline, CNG, methanol

[10] In fact 717 respondents finished phase 2, but a handful of them provided incomplete choice data.

Table 1.2. Nested Multinomial Logit model by Bunch et al. (1993)

Variable	Model 1	
(variable^2 means square of variable)	coeff.	p-value
Purchase price ($1000)	−0,134	0
Fuel cost (cents/mile)	−0,190	0
Range (100 miles)	2,52	0
Range^2 (100 miles)^2	−0,408	0
Emissions level (fraction of current)	−2,45	0
Emissions level^2 (fraction of current)^2	0,855	0,007
Fuel availability (fraction of stations)	2,96	0
Fuel availability^2 (fraction of stations)^2	−1,63	0
Alternative fuel (constant relative to gasoline veh.)	0,098	0,368
Multiple fuel (constant relative to gasoline veh.)	0,693	0
Electric vehicle (constant relative to gasoline veh.)	−0,024	0,92
Hybrid electric (constant relative to gasoline veh.)	−0,257	0,134
Electric: charge at work as well as home (dummy)	−0,126	0,271
Electric: low performance (dummy)	−1,04	0
Electric: low performance with hybrid (dummy)	0,544	0,022
Non-electric vehicles (log-sum coefficient λ)	0,805	0,001

and electric. A two-phase survey setup was applied. The first phase was completed by 7387 households approached through random dialling and collected household information through CATI[11]. In the second phase a choice set with six alternatives described by 15 attributes was sent to the respondents. The response rate in the second phase was 66%, providing a net sample with sufficient non-missing information of $N = 4654$.

In Brownstone et al. (2000), revealed preference (RP) data have been added to develop a joint estimation mixed logit model.

1.3.2. Canada

Ewing and Sarigöllü (1998) designed a vehicle technology choice model for the Montreal metropolitan area. The model was estimated using a SP data set that was built on a survey with 1500 respondents in the suburbs of the Montreal Census Metropolitan Area. The survey applied a two phase approach similar to Brownstone and Train (1999). Of the 1500 phase one respondents, 59% completed the second phase of the survey, which consisted of completing nine choice sets. The choice sets presented a choice between three alternative technologies described by 8 attributes.

[11] Computer-aided telephone interview

Table 1.3. Multinomial Logit Model by Brownstone and Train (1999)

Variable	coefficient	*p*-value
Price/ln(income)	−0,185	0
Range	0,350	0
Acceleration	−0,716	0
Top speed	0,261	0,001
Pollution	−0,444	0
Size	0,935	0,003
Big enough	0,143	0,06
Luggage space	0,501	0,008
Operating cost	−0,768	0
Station availability	0,413	0
Sports utility vehicle	0,820	0
Sports car	0,637	0
Station wagon	−1,437	0
Truck	−1,017	0
Van	−0,799	0
Constant for EV	−0,179	0,290
Commute<5 × EV	0,198	0,016
College × EV	0,443	0
Constant for CNG	0,345	0
Constant for methanol	0,313	0,002
College × methanol	0,228	0,010

The model includes vehicle technology and commuting attributes, allowing for the assessment of infrastructure related policies, e.g. separate motorway lanes for cleaner vehicles. The number of vehicle technology types included in the survey is limited to three: a conventional gasoline vehicle, an electrical vehicle and a more fuel-efficient vehicle running on gasoline or alternative fuel.

Several multinomial logit model specifications were estimated: starting with a basic model with main effects only, both for categorical and continuous variables for some technology attributes. Next a choice model was estimated including several interaction terms. The choice process was also tested for correlation in preferences for vehicle types, but with negative results. As a result, no nested logit specification was found appropriate.

The coefficient estimates of the basic multinomial logit discrete choice model with continuous variables can be found in table 1.4.

1.3.3. Norway

A technology choice model has been developed by Ramjerdi and Rand (1999) to estimate demand for clean fuel cars in Norway. Both MNL and NL models have been estimated. Three fuel technologies were included: gasoline, electric and alternative fuel. Different models were estimated for the household's main car (table 1.5) and for the second car.

The survey implemented a two phase approach similar to Ewing and Sarigöllü (1998). Choice sets consisted of three alternatives with 8 attributes. The sample size used for multinomial logit estimation used data from 1222 observations.

This study identifies a correlation in preferences for non-electric vehicles, a nesting structure that is identical to Bunch et al. (1993).

Table 1.4. Multinomial logit model by Ewing and Sarigöllü (1998)

Variable	coefficient	p-value
Fuel-efficient vehicle constant	0,42	0
Electric vehicle constant	0,25	0,009
Price ($)	−0,00022	0
Maintenance cost ($/year)	−0,00104	0
Acceleration (as % of current car)	0,013	0
Range (miles)	0,0039	0
Refuel time (minutes)	−0,0014	0
Emission rate (as % of current car)	−0,7128	0
Commuting time (min one-way)	−0,008	0,024
Commuting cost ($/week)	−0,015	0

Table 1.5. (M)NL model for HH main car by Ramjerdi and Rand (1999)

Variable	MNL		NL	
(var^2 means square of var)	coeff.	p-value	coeff.	p-value
Constant, electric car	−2,351	0	−2,2030	0
Constant, alt fuel car	−1,348	0	−1,0450	0
Electric car, refuelling range	0,04089	0	0,0391	0,001
Gasoline car, emission	−0,1888	0,272	−0,2971	0,089
Gasoline car, HH without car	−1,786	0	−1,6120	0
Gasoline car, age over 66	0,5457	0,046	0,6355	0,028
Alt fuel car, refuelling range	0,02495	0	0,0256	0
Gasoline, HH income			0,0015	0,036
Purchase price	−0,009577	0	−0,0115	0
Variable car cost	−0,008816	0,842		
Number of seats	0,4200	0	−0,7337	0,058
Number of seats^2			0,1597	0,005
Top speed	0,0992	0,004	0,1112	0,004
Accessibility	0,3808	0,028		
Logsum λ (non-electric veh.)		0,6566	0	

1.3.4. UK

Batley et al. (2003) estimated a discrete choice model for alternative-fuel technologies based on a UK survey conducted by Knight (2001). Different specifications of multinomial logit, nested logit and mixed logit models have been estimated.

The survey methodology differs somewhat from most other studies. The choice sets were limited to two alternatives with four properties (variables), this in order to limit cognitive difficulty for the respondent.

The alternatives were unlabelled in the choice sets. However, the levels of the variables differed between both alternatives in such way that the *alternative* car was distinguishable, an effect that was confirmed in model estimation by finding a significant dummy coefficient.

In order to allow for seven variables in the choice model estimation, the variables were divided over two setups with four variables each, having the purchase price in common. The nested logit specification was used in order to allow for integration of both setups in model estimation, following a methodology proposed by Bradley and Daly (1991). This comes down to introducing a scaling factor (the log-sum coefficient) for the expected utility V_{jmn} (see equation (1.1)) of the alternatives belonging to one of both setups. For completeness we provide here the resulting multinomial logit model in table 1.6.

Table 1.6. Multinomial logit model by Batley et al. (2003)

Variable	coefficient	p-value
Purchase price	−0,215	0
Operating costs	−0,072	0
Maximum speed	0,143	0
Fuel availability	0,234	0
Emissions	−0,212	0
Range	0,478	0
Refuel location	−1,22	0
λ (log-sum)	0,642	0

1.3.5. Summary

Past research provides much insight in discrete choice modelling of new private car technologies. We see that a short-list of choice variables is common to most studies: purchase cost, range, etc. The survey procedure applied shows much similarity between the different studies. Nested logit model estimations identify a correlation in preferences for non-electric cars as opposed to electric cars.

There are however some limitations. As the emphasis has been put on alternative fuels rather than on alternative technologies, hybrid cars seem not to be covered by most past research, Bunch et al. (1993) being the sole exception. We also observe that most past research focused on car markets where only one technology (gasoline) was available for private cars at the moment of the survey. None of the studies mentioned did study differences in the correlation between two or more established technologies (e.g. diesel and gasoline) at one hand and alternative technologies at the other hand. Finally, most studies did not cover all cost variables, in most cases excluding annual costs such as maintenance which may differ significantly between technologies (e.g. replacement of battery pack for electric car).

As far as we could identify, alternative technology choice for private cars has not been researched yet for Belgium. The survey described in the next sections allows to build the necessary data set for estimation of a choice model for the Flemish car market. The approach used is similar to the literature surveyed, however we modified the methodology on some points in order to overcome the limitations identified above.

1.4. Focus group

In this section we report on the *focus group* session that was held in preparation of the survey. The aim of this focus group was to analyse qualitatively the choice process consumers experience upon buying a new car. Starting from very general aspects of choosing a new car, the focus of the discussion moves gradually towards the more technical aspects of choosing between different technological makes of the same car type. Finally two choice set designs were tested with special focus on terminology used and layout design.

The focus group discussion was held at a weekday evening in Antwerp in spring 2004. The size of the group was $N = 7$. The main criterion for the selection of participants to the focus group was the purchase of a new car during the last year (including having made the decision on make, brand and type) and being the owner as well as the main driver of that car. To allow for a balanced discussion, the selection of participants for the focus group was gender balanced.

At the start of the session the focus group was initiated as a spontaneous discussion on why the participants bought a new car. As the issue was risen which aspects a potential car buyer should consider when choosing a car, a long list of characteristics were discussed, ranging from size, comfort, driving characteristics, family size, car body colour to safety and maintenance cost. Already at this point there was a small discussion regarding repair and maintenance costs to expect, and how the related risk can be covered by a *service package*.

Starting from the extended list of car variables, the discussion was further narrowed towards the more technological properties and how these were assessed by the participants. As the session proceeded, the discussion was gradually moved from the first list of car variables to some aspects that had not been risen spontaneously to cover their assessment as well. In this section we will report on car properties that are relevant for the design of our survey.

Fuel consumption was one of the first aspects discussed. The participants indicated that this was rather simple to assess, as plenty of information is available, although it was remarked that there is a relation with the driving style of the driver as well.

Expected annual *mileage* was indicated to have a relation to the choice between gasoline, diesel and LPG cars. Also the relation between fuel and first or second car was made. Another aspect linked to fuel choice was family tradition.

Upon choosing between cars, the buyer apparently first decides on the *car body* and next chooses within that segment for a technical version.

The *engines size* (in cc) was indicated as a choice variable, being linked first to taxes but having relation also with power and driving comfort. *Driving comfort* itself was however related to a lot of other aspects as well, including air conditioning, sense of space etc.

Regarding *reliability*, the question was raised if there still is a real difference between new cars now available on the market.

Different aspects of the *user cost* were discussed. Some car buyers apparently thoroughly compare all available figures, whereas others trade-off financial aspects in a less rational way. A distinction between purchase, annual and distance related costs was made, but also other aspects were included in the decision, e.g. not only the average annual maintenance cost matters, but also the maintenance interval is relevant as it determines the owner's time costs of bringing the car to the service centre. Some of the more irrational aspects mentioned included the absolute cost of filling up at the gas station (rather than the per kilometre cost). The fact that large price differences exist between cars sold by different car dealers, making a comparison more difficult, was also taken into account.

Another interesting issue was the uncertainty about future taxes. Apparently this issue is considered by some car buyers.

Raising the issue of retrofitting the new car for *LPG* use, the participants made a link with loss of luggage space, although it was immediately added that this loss can be limited. LPG was further considered as cheaper in use and better for the environment. However, it was added that LPG still excludes access to some underground parking infrastructure.

Discussing the *emissions* issue, the Euro emission class was immediately determined as the main indicator. For diesel cars the participants added not to like too much visual soot-emissions. However, it was indicated that not much information is available for car purchasers regarding emissions.[12]

Some *technological subclasses* of conventional diesel technologies currently available had already been mentioned, so the participants were asked to judge the difference between injection, turbo, ecopower, etc. Besides power and driving performance the respondents added fuel efficiency as an important characteristic.

The *hybrid technology* was linked immediately to higher purchase price, better fuel efficiency and better environmental performance. Some uncertainties were added: has technology matured, is power sufficient and what about battery replacement costs? Different driving performance characteristics are expected but the participants thought this can easily be overcome after some time (learning curve effect). It was added that an incentive may be needed to convince the car purchaser, e.g. a subsidy or lower insurance costs.

The final aspect to be discussed was *alternative fuels*. A first fuel mentioned was *vegetable oil* and hydrogen. For *hydrogen* it was immediately questioned how safe its use is and if its technology is reliable. It was further added that infrastructure needs to be adapted (gas stations). *Solar energy* and *electricity* were also identified as alternative fuel, but again the infrastructure issue was raised. *Ethanol* and *methanol* were identified as *involving risk of life*—although it was immediately added that this was probably a psychological judgement rather than a rational one. The analogy with LPG was made, where studies

[12]It may be useful to add here that no distinction between Euro classification for gasoline and diesel was made—apparently the common denominator for both fuels suggests common standards which is actually not the case.

have proved that gasoline and diesel are actually less safe in use.[13] However, these fuels obviously do not provide a comfortable feeling to the car buyer.

Overall the alternative fuels were assessed as still too experimental at this point in time. All in all there seems to be much uncertainty related to them: at what cost will they come, how broadly will they be available, what will be the reliability of the related technologies. More information is needed to make a more thorough assessment.

In the last part of the focus group session a *simulation exercise* was conducted. Two choice set setups were prepared based on the literature: one containing three alternatives and another one with five alternative technologies. The setup with three alternatives was motivated based on the literature review where most past research used this approach. A setup with more alternatives however provides more information on the choice behaviour of the respondent, but this also increases the cognitive difficulty of the choice task, which in turn may result in a less deterministic choice behaviour. We therefore decided to test such an extended setup in the focus group session and to observe the participant's reaction to both setups.

A small preliminary test of the designs had already been held before the focus group session and some improvements (especially regarding layout) had already been identified and implemented in the version proposed to the focus group participants.

The choice sets were presented to the focus group participants and they were asked to consider them. After the participants made their choice, the choice sets were discussed. The main goal was to see if the design of the sets was clear and if five alternatives wasn't too difficult from a cognitive point of view.

The number of questions for clarification indicated that *unambiguous formulation* of the different aspects is necessary. It is important not to leave too much space is left for interpretation by the respondents. This would make estimation of a discrete choice model much more difficult (especially considering the limited survey budget). Take as an example the car taxes, for which the participants indicated that it should be clearly mentioned if they are included or not in the cost figures provided in the choice sets.

As for *emissions*, an alternative formulation of this variable seemed important. The design as it was presented in the focus group provided environmental costs per kilometre as a measure for emissions level, but this was confused with a monetary user cost.

Fuel availability was included in the focus group choice set design. The discussion of the variable indicated that this was also a difficult one to represent objectively. The participants indicated that the share of fuel stations having the fuel was irrelevant for them: the only thing that matters is whether the

[13] We report this as discussed in the focus group—any studies suggested here are unknown to us.

station around the corner has it or not.

Finally there was some surprise for us when the participants indicated the choice set with *five alternatives* to be an easier task compared to the one with three alternatives. It was felt to be more realistic to have about five alternatives when it comes to technology choice rather than just three. Although it was added that there may have been a relation to the combination of levels of the variables in the particular sets designed for the focus group.

1.5. Survey

In this section we discuss the survey design and implementation.

1.5.1. Targeted statistical population

The *population* for the survey are the households living in Flanders. We include *all* households in the population: the current car ownership status of the household is not considered. This means that we also include households who own a second hand car of do not own a car at all at the moment of the survey.

1.5.2. Observation method

The choice information is collected in a *two phase* survey conducted in spring 2004.[14] A *first* phase (sample $N = 257$) invites the respondent to participate in the survey, and collects some socio-demographic data, together with information that should allow for customisation of the second phase (see 1.5.7). This first phase is conducted making use of CATI[15].

In the *second* phase the respondent is sent six (customised) choice sets by mail.[16] Each of these sets presents a choice between five alternative vehicle technologies, with for each alternative a value for each technology variable. A CATI is then used to ask the respondent which vehicle he would buy in case the purchase of a new vehicle would be necessary at the time of the survey. 209 respondents completed the second phase of the survey.

A small *pilot* ($N = 19$) has been conducted in order to check the survey procedures before the full test is held. The main result of the pilot was an overhaul of the quality control procedures.

[14]This two phase approach is similar to what has been applied in most past research (see section 1.3)

[15]Computer Aided Telephone Interview

[16]The design of the choice sets is discussed in section 1.5.7; a choice set example is provided in appendix B.

1.5.3. Sampling frame

In order to allow for representative survey results, a proper sampling frame has to be chosen. This frame has to cover the statistical population as completely as possible.

The respondents are selected through a CATI in phase 1 by dialling randomly selected listed phone numbers. This means that the frame for the sample are the households in Flanders having a fixed telephone connection. Limiting the dialling procedure to listed phone numbers allows to exclude non-existing as well as non-residential phone numbers which greatly enhances the efficiency of the selection procedure. It also allows to efficiently control the urbanisation stratification variable.

The use of this frame has the disadvantage that people who have no (listed) telephone number can not be selected. Households who have more than one fixed line have theoretically more chance to be selected, be it that the second line is probably mainly used for fax and/or internet use and thus won't be answered upon calling. Moreover, literature provided no evidence on the existence of a correlation between car technology choice and the number of fixed telephone lines. Nevertheless we have to take these disadvantages into account when determining the sampling method to avoid a bias.

1.5.4. Sampling method

Different sampling methods are possible. The *stratified sample* seems to be the most appropriate for our survey.

The stratification has been done on the basis of household income, as this variable is relevant for car technology choice preferences. For Flanders, this is a variable that is very difficult to determine directly in a survey, the risk of ending up with no usable information is significant. This problem has been addressed by using the standard demographic classification by ESOMAR (1997). This methodology is used to determine the appropriate *Social Grade* category of the *Main Income Earner* in the household (M.I.E.). The Social Grade variable is a composite variable based on:

- the occupation of the M.I.E.;
- the Terminal Education Age of the M.I.E., adjusted to incorporate any further education or professional training completed by the M.I.E. following a period of employment;
- in the case of non-active M.I.E.s, the Economic Status of the household, based on the household ownership level of ten selected consumer durables.

We used a standardised questionnaire to determine the Social Grade category of the respondents. For these categories, the average household income is available from statistics.

Further stratification is made regarding the respondent's age, gender, province and degree of urbanisation. We also included the choice set blocking variable in the stratification process (see section 1.5.7).

We want each stratum to be represented *proportionally* in the survey. Therefore the quota have to be calculated, based on the targeted total number of respondents and the shares of the different strata in population statistics. Filter questions have been added in the first phase in order to determine the strata (see 1.5.6). The stratification quota were set based on the original sample target for phase two, which was $N = 150$.[17] As the response rate in the second phase turned out to be higher than expected, a final sample of $N = 209$ could be realised.

1.5.5. Sample Size

In the literature we find an indication of the number of respondents that typically enter the data set used for estimation of technology choice variables. An overview is provided in table 1.7.

Given the limited survey budget, we asked each respondent to deal with six choice sets. This way, we were able to get 1254 observations (209 respondents, 6 sets per respondent).

The decision to send each respondent six choice sets involves some risk by inducing correlation between in choices by the same respondent. For the multinomial and nested logit specification, the estimation of standard errors (and p-values) for the coefficients relies on strict independence between observations, and may therefore be understated. The estimation of the coefficient values however will not suffer from this. Therefore the benefits of a larger data set will more than outweigh this concern (Bunch et al., 1993).

[17]The variables enter the stratification *uncrossed*, that is: in the sampling procedure each stratification variable is checked independently. Given the small sample size, a crossed stratification would result in more strata than respondents.

Table 1.7. Data set size in literature

Study	data set size (number of observations)
Bunch et al. (1993)	3460
Brownstone and Train (1999)	4654
Ramjerdi and Rand (1999): main car model	1197
Ramjerdi and Rand (1999): second car model	945
Ewing and Sarigöllü (1998)	7856

1.5.6. Data collection procedures

Besides the questions that collect the data necessary for the model estimation, we included some filtering questions in the beginning of the CATI in phase 1, in order to control the stratification of the sample. In case the quota for a stratum have been reached, any further respondent belonging to that stratum was refused to participate.

The initial sampling procedure randomly selects listed phone numbers over the whole of Flanders (all provinces). However, when the quota for a given province is reached, the sample procedure was adapted in order to exclude the selection of telephone numbers that are geographically situated in that province. This increased the efficiency.

1.5.7. Choice set design

The design of the *choice sets* for the survey is discussed in this section. These choice sets include five vehicle technologies. Each respondent indicates for each choice set the technology of his/her choice.

The design of the choice sets has to meet some objectives:[18]

- minimise the level of cognitive difficulty;
- maximise the credibility of the choice alternatives;
- maximise the numbers and types of choice models (e.g. different nesting structures, utility functions) that can be estimated from the final data set;
- maximise potential simulation flexibility;
- maximise statistical efficiency.

In a first subsection we select the technology variables to be included. In the second subsection, the levels of the variables in the choice sets are fixed and in the last subsection we discuss how the levels of the variables are combined in the final choice sets.

Technology variables

Earlier research on the topic (see section 1.3) provides us with an indication of the technology variables that are relevant for the choice we want to model. These variables proved to be significant in choice models estimated based on stated or revealed preferences data.

We also use the focus group observation (see section 1.4) to identify the variables considered by consumers purchasing a car.

Further, expert discussions have been held regarding which variables to include.

[18] Based on Bunch et al. (1993)

Finally simulations have been conducted in order to identify the number of variables that can be estimated simultaneously given the limited budget (and hence limited sample size).

All these considerations resulted in a final list:

- *Engine type* and *energy source*: the combination of these variables was used to describe internal combustion engine technologies running on different fuels as well as fuel cell and battery electric technologies (see table 1.8 for an overview). In model estimation (see section 1.6) we will specify a separate dummy[19] for each technology.[20] For the internal combustion engine technologies, the energy source can be gasoline, diesel, LPG[21] or an unspecified alternative fuel. Fuel cell technologies are defined as running on the alternative fuel. Electrical battery technology is powered with electricity and it was specified that batteries are recharged at home, an operation taking several hours. For the other technologies, refuelling time was defined as equal, fuel storage being as safe for all alternatives and all fuels available at all service stations in Europe. We remind the reader that an outcome of the focus group (see section 1.4) was the decision that an unambiguous definition of all variables was necessary, hence the sometimes rather extended specifications (see appendix B for the exact formulation). We decided not to further specify the alternative fuel because in the focus group methanol, ethanol etc. all sounded alike for the participants, who added that they probably don't know anything about them at all.

- *Power train (transmission)*: conventional or hybrid (for ICE[22] only), in the estimation we will include a dummy for hybrid transmission. Hybrid was specified as a combination of an electric and internal combustion engine driving the wheels. It was further specified that the internal combustion engine recharges the batteries. Motivation for this specification was based on the characteristics of the only hybrid car available on the market at the moment of the survey (Toyota Prius), in order to avoid

[19]Where we discuss or apply discrete choice theory we will use the terminology that is common in the literature (for instance K. E. Train, 2003). A *dummy* choice variable for alternative j is a variable whose value in the representative utility of alternative i is $d_i^j = 1$ for $i = j$ and zero otherwise. It could be understood as a *binary* variable.

[20]From equation (1.2) it is easy to derive that the coefficient of one alternative-specific dummy is undetermined (linear combination of remaining dummies), we will hence omit the dummy for gasoline. This results in dummy coefficient values to be relative to the gasoline internal combustion engine technology.

[21]Technologies are represented as single-fuel in the choice sets. For retrofit LPG and CNG cars, this assumption seems not to meet today's common specifications, which allow the use of gasoline. However, people owning such car are likely to use the alternative fuel most of the time because that fuel is much cheaper in Belgium (otherwise they probably would not have retrofit their car).

[22]Internal Combustion Engine

Table 1.8. Technology type represented by engine type and energy source in the survey

Technology	Engine type	Energy source
Gasoline	Internal combustion	Gasoline
Diesel	Internal combustion	Diesel
LPG	Internal combustion	LPG
Alternative fuel	Internal combustion	Alternative fuel (unspecified)
Battery	Electrical	Electrical energy from batteries
Fuel cell	Electrical	Fuel cells convert an alternative fuel into electrical energy

confusion on the topic. We also refer to Burgwal et al. (2001) providing some evidence that hybrid technology is evolving towards the use of smaller battery units, used as a temporary power storage buffer only and not allowing to recharge the batteries at home or at another place.

- *Purchase cost*: purchase cost in euro including VAT and registration taxes. It was indicated that bargains and subsidies were reflected in the purchase cost.

- *Annual cost*: annual cost in euro, all taxes included. Based on focus group observations we formulate repair, maintenance and battery replacement costs as an annual service plan fee included in the annual cost variable, this reduces the risk perceived by the consumer related to the purchase of new technologies. It was further specified that the frequency of maintenance was the same for all technologies.

- *Fuel cost*: fuel cost per kilometre in euro, including all taxes (excise and VAT). It was specified that these fuel costs assume a normal driving style.

- *Range*: distance driven without refuelling, in km. Again we added that this distance assumed a normal driving style.

- *Emissions level*: damage by exhaust emissions from the car. The focus group indicated that special attention should be paid to the formulation of this variable. We decided to express emissions damage as relative to the damage caused by the average new gasoline car sold at the moment of the survey.[23] To avoid further confusion the emissions damage of the gasoline car in the choice sets was constant and specified as equal to the level of the average car sold at the moment of the survey. For diesel cars we specified emissions damage in a similar way as equal to the level of the average diesel car sold. Motivation here was the focus group observation that car buyers seem no to be informed on the

[23] This is a Euro 3 car.

major difference in emission damage level of diesel relative to gasoline technologies: we would have to specify levels of several hundred percent to compare diesel to gasoline, this may not only introduce a cognitive difficulty (percentages over 100% might be confusing), but it may fail to reproduce the observed real world choice situation where consistent information on the environmental damage difference diesel-gasoline is absent.

- *Trunk space*: loss of trunk space because of technology related requirements, e.g. gas tank (not for ICE on conventional fuels), expressed as a percentage relative to a gasoline or diesel car's trunk space.

We also provide a motivation for the exclusion of some technology attributes in the final choice set specification:[24]

- *Fuel availability*: the focus group provided evidence that this is a variable which is difficult to express.[25] As a simulation exercise indicated that with the given survey budget we might fail to estimate coefficients for a too large number of variables, we decided to drop this variable from the choice sets.

- *Driving performance*: the focus group indicated that a lot of technology variables are linked to driving performance, making it more difficult to provide a single measure that acts as a proxy for overall driving performance. Further on, some of these variables such as engine size (in litre) are closely associated with taxation levels and should hence be avoided in a stated preference setting. We finally decided to exclude this variable because earlier revealed preference research[26] provides information on the trade off between driving performance and purchase cost for the Flemish market. This attribute varies amply over conventional technologies and new alternative technologies will probably not fall beyond observed values.

- *Reliability*: the focus group did not consider this variable in detail. It was decided from the beginning to define all technologies as equal.

Based on the literature review and the focus group observation, we believe that the variables that we finally selected for the choice sets describe the technology choice decision to a sufficient degree.

[24]For these variables we specified in the survey that they do not differ over alternatives in the choice sets.

[25]Maybe we should add here that this variable is an attribute of service stations rather than private car technologies. The interest of such a variable for analysis of choice behaviour and policy simulations seems somewhat limited—more limited than for the other variables.

[26]Some references: Verboven (1996), G. De Ceuster et al. (2005)

In the next section we will discuss the orthogonal setup of the variables in the choice sets. It is important to note that as a result of this setup the omission of one or more variables has no impact on the estimation of the other variables, so even if we miss out on an important choice determinant, this will not affect the assessment of the impact of the other variables on the choice made. In the model estimation (see section 1.6) we will include some dummy variables. The role of the dummies in model estimation is to capture all choice preferences that could not be explained by the generic and/or interaction variables.

We finally note that the number of variables (9) is smaller than what has been applied successfully in literature (Brownstone and Train, 1999), so from the point of view of cognitive difficulty we should be on the safe side.

Levels of the technology variables in the choice sets

Based on literature review and focus group results, we have chosen for a design with five choice alternatives per choice set. Each choice set includes a gasoline, diesel, LPG and an alternative fuel car. The fifth car is either a fuel cell or a battery powered car.[27]

We now have to fix two or three levels at which the different technology attributes enter the choice sets. Two levels allow for a linear estimation only, whereas for variables that have three levels a quadratic term can be estimated as well.

The levels have to be specified in such way that they are meaningful to the respondent on the one hand. On the other hand, the values of the attributes of the technologies we want to simulate (see technological scope in section 1.2.1, for a description of the technologies we refer to appendix D) have to be as much as possible within the range we apply in the survey. The choice of three levels for each variable should allow us to cover the range of interest and at the same time allow us to estimate for non-linear effects. The range of levels has thus to be chosen wide enough to allow for forecasting flexibility, but at the other hand not too wide because that would undermine statistical efficiency as well as the credibility for the respondent. Finally, domination of the variation of one variable in the choice process should be prevented, e.g. if the variation of the purchase cost is too big compared to the variation of the other variables, the respondent may consider only purchase cost and as a result we would not get any information on the influence of the other variables. Past research (see section 1.3) provided an indication on the trade-off of the different technology attributes.

The values used in the survey are presented in table 1.9.

[27] This setup where two technologies each enter half of the choice sets is similar to the setup by Bunch et al. (1993). We will have a closer look to possible consequences of such a setup when we discuss the model estimation (see 1.6.3).

The levels of the *purchase cost* are relative to the value of B, which is the amount the respondent indicated in the first phase of the survey he/she would spend in case the respondent had to buy a new car at the moment of the survey, with a minimum of 10 000 € and a maximum of 30 000 €. In case of non-specification, a default value of 10 000 € was applied. This customisation of the choice sets was introduced in order to enhance the credibility of the choice task.[28]

The annual costs were also defined proportional to B. The average value of 15% of the average purchase cost is based on the TREMOVE 2 model (G. De Ceuster et al., 2005).

All cost variables have been represented both in euro and Belgian franc, as the focus group clearly indicated that people still commonly use the now obsolete Belgian franc for valuation.

The exact layout and formulation (in Dutch) of the choice sets is provided in appendix B.

Factorial design

The choice set setup results in eight variables with two levels and twenty variables with three levels. In this section we will discuss how the combinations of the different levels for the final choice sets are designed.

When we would apply a full factorial design, this would result in a huge number of runs. A full factorial would result in $3^{20} \cdot 2^{8}$ runs, which falls beyond any existential limits.

However, a full factorial design is necessary only in case we want to estimate all (interaction) coefficients. For the purpose of the car technology choice model we limit our focus to the main effects, assuming that all interaction coefficients between variables in the choice sets are zero.

For that reason, we apply an orthogonal main-effect plan.[29] A main effects plan for this design has been selected with SAS (SAS Institute Inc., 2001) and is limited to 72 runs. This plan also included a blocking variable with twelve levels (six choice sets per respondent).

In a final step, the choice sets are customised (cost variable B) and the order of technologies as well as technologies variables are randomised within each choice set, in order to prevent any order-related bias.

[28] The deliberately low default value avoids that the respondent is presented with cost values that are too far beyond his or her budget.

[29] An orthogonal main-effect plan is an orthogonal fraction of resolution III. In such a design the levels of the variables are uncorrelated, which is a major advantage as it allows for uncorrelated estimation of the coefficients in section 1.6, under the assumption that all interactions are absent. A more extended discussion on the topic can be found in Day (1985).

Table 1.9. Levels of the variables in the choice sets for each technology type

Variable	Car 1	Car 2	Car 3	Car 4	Car 5
Engine	ICE	ICE	ICE	ICE	Electrical
Energy	Gasoline	Diesel	LPG	Alternative fuel	Batteries Fuel cells
Transmission	Conv Hybrid	Conv Hybrid	Conv Hybrid	Conv Hybrid	Electrical
Purchase cost	0,85B B 1,15B	0,85B B 1,15B	0,85B B 1,15B	0,85B B 1,15B	0,85B B 1,15B
Annual cost	0,135B 0,15B 0,165B	0,135B 0,15B 0,165B	0,135B 0,15B 0,165B	0,135B 0,15B 0,165B	0,135B 0,15B 0,165B
Fuel cost	0,05 0,07 0,10	0,05 0,07 0,10	0,05 0,07 0,10	0,05 0,07 0,10	0,05 0,07 0,10
Range	500 km	500 km	500 km 300 km 200 km	500 km 300 km 200 km	500 km 300 km 200 km
Emissions	100%	Diesel	25% 50% 100%	25% 50% 100%	0% 0% 0%
Trunk space	100%	100%	100% 30%	100% 30%	100% 30%

1.6. Model estimation

In this section we use survey estimated choice models to analyse the choice making behaviour.

To compare different models we use the *log-likelihood* statistic. This is a strictly negative value, with a higher figure (or smaller in absolute value) indicating a better model fit.

Any statement regarding significance of coefficients and model improvements in this section is considered at $p \leq 0{,}05$.

Different variables will enter the estimation process, we will divide them in three clusters (see table 1.10). First we have the *generic variables*, these are the technology attributes that enter the deterministic utility V_{jmn} as continuous variables and for which no alternative-specific coefficients will be estimated (i.e. one generic coefficient). Although given our factorial design (see section 1.5.7) it is possible to estimate alternative specific coefficients, we will limit our analysis to generic coefficient estimations in order to limit the number of coefficients to be estimated.[30] This approach is in line with past research (see section 1.3) where the focus was on generic coefficients.

The second group of variables are the *dummies*. They enter the deterministic utility V_{jmn} as a binary variable (value 0 or 1). These variables represent the technology type (e.g. hybrid). Most of them are by definition alternative specific, an exception being the hybrid technology dummy for which a generic coefficient will be estimated.[31]

The last group of variables are the *interaction variables*. These are generic variables or dummies that interact with a respondent specific attribute (hence the n in V_{jmn}). We will motivate the selection of interaction variables further down this section.

We will start with a simple multinomial logit specification, next move to a nested logit setting and finally study mixed logit models.

[30]Note that the the selected factorial design (see table 1.9) treats battery and fuel cell technologies as a single alternative (Car 5) with the energy source as a variable. Because of the main effects only factorial plan it would not be possible to estimate specific coefficient values for battery or fuel cell technologies for the other variables (such as a battery-specific coefficient for range) describing the alternative.

[31]Technically the dummies for *fuel cell* and *battery* are attributes of the fifth choice alternative in the factorial design (see table 1.9). We will threat them in our analysis as if they were genuine alternative specific dummies.

Table 1.10. Variables in model estimation

Generic variables	Purchase cost
	Annual cost
	Fuel cost
	Available luggage space
	Emissions
	Range
	Hybrid
Dummies	Diesel
	LPG
	Alternative fuel
	Fuel cell
	Battery
Interaction variables	Emissions × woman
	(diesel or alternative) × man
	Battery × class<5
	Luggage × class<5
	Emissions × family size>3
	Luggage × family size>3
	(diesel or LPG or alternative) × family size<4

1.6.1. Multinomial logit

A first multinomial logit specification is limited to the generic variables and dummies which enter the deterministic utility V_{jmn} in a linear way. The second step is to allow for quadratic terms, after which we study the introduction of interaction variables.

First Degree: the linear terms

The stated preference data set collected in the survey was first used to estimate a multinomial logit choice model with all generic variables and dummies (see section 1.5.7) entering the utility function in a *linear* way. We used the STATA application (Stata Corporation, 2002) for all model estimations, the resulting coefficients are in table 1.11.

We see that all the *generic variables* enter the model significantly. The sign of their coefficients is acceptable. Negative signs are observed for all cost variables and emissions, meaning that an increase in the value of these variables decreases the deterministic utility V_{jmn} of the choice alternative (recall formula (1.2)).

The significance of the emissions coefficient together with the negative sign shows that the respondents of the survey prefer cleaner cars over more polluting ones all other things being equal. This result is in line with earlier studies (see section 1.3). However, we should remind that we are working in a stated preference setting. Batley et al. (2003) suggest that for this issue stated preference results may differ from actual purchase behaviour. Respondents may choose a socially-acceptable alternative rather than what they would buy in a real world setting. Based on focus group findings a formulation for the

Table 1.11. Multinomial logit choice model

Variable	Unit	Coefficient	p-value	95% conf. interval	
Purchase cost	1000€	−0,1224	0	−0,1557	−0,0891
Annual cost	1000€	−0,5031	0,003	−0,8336	−0,1727
Fuel cost	€/km	−10,6868	0	−13,9568	−7,4168
Luggage space	0–1	0,9934	0	0,7044	1,2823
Emissions	0–1	−0,8575	0	−1,3075	−0,4076
Range	100km	0,2614	0	0,1852	0,3376
Diesel		0,4641	0	0,3145	0,6138
LPG		−0,8228	0	−1,1633	−0,4822
Alternative fuel		−0,3325	0,039	−0,6486	−0,0163
Fuel cell		−0,1507	0,571	−0,6721	0,3707
Battery		−0,4041	0,131	−0,9286	0,1203
Hybrid		0,0025	0,974	−0,1446	0,1496
Log likelihood		−1751,8061			

emissions variable was chosen in order to avoid such associations as much as possible (see section 1.4).

The 95% confidence interval provides an indication of the influence of the sample size (209 respondents) on the estimation results: it indicates the range around the estimated value in which the real coefficient (of the whole population) is with a probability of 95% for a random sample. The confidence interval is linked with the p-value: a 95% confidence interval that has 0 as delimiting value will result in a p-value of 5%.

For the *dummies* only the diesel, LPG and alternative fuel coefficient differ significantly from zero ($p \leq 5\%$). This means that we could not measure a significant preference (be it positive of negative) for fuel cell, battery and hybrid cars that is not the result from differences in the values of the generic variables (e.g. purchase cost). For the fuel cell and the battery cars this is not too surprising, as these dummies concern only one choice alternative in half of the choice sets, the amount of information on the influence of these properties is hence limited. The hybrid dummy however is present for four choice alternatives in every choice set. The hybrid property does clearly not have a significant influence on the choice outcome. This finding is in line with focus group observations. We will come back to the preferences for hybrids in section 1.6.3.

Both the LPG and alternative fuel dummies have negative coefficients, meaning that these choice alternatives have a lower deterministic utility V_{jmn} compared to the gasoline alternative (which has no alternative specific dummy and serves as the reference alternative) when all other properties are equal (purchase cost, emissions, etc.). The diesel dummy coefficient has a positive sign, which may be explained by reference dependence considering the large share of diesel cars in the current stock (see section 1.6.3).

The *willingness to pay* (WTP) for a change in the value of the different variables can be calculated by dividing the corresponding coefficient by the purchase cost coefficient. The ratio of the coefficients of two variables is a measure for the trade-off that is made by the respondent: the respondent is indifferent to the corresponding changes as the net impact on deterministic utility V_{jmn} is zero (see formula (1.1)). The resulting WTP is shown in table 1.12 for selected choice variables.

For emissions we observe a willingness to pay of €701 for a 10% reduction which is about half of what has been observed in California (Bunch et al., 1993) or UK (Batley et al., 2003). For luggage space there is a willingness to accept of €811 for a decrease in luggage space of 10%. Similarly a reduction in range of 100 km is valued at €2136, which is in line with Batley et al. (2003) and about half of Bunch et al. (1993).

The dummy coefficients provide rather high WTP estimates. There is clearly opposition against LPG, which was somewhat expected based on observed discussions in the focus group. It seems that LPG cars still bear

Table 1.12. WTP in multinomial logit technology choice model (in €)

technology change	WTP in €
reduction in trunk space of 10% (compared to diesel/gasoline car)	−812
reduction in emissions of 10% (compared to gasoline car)	701
100km shorter range	−2136
diesel instead of gasoline	3770
LPG instead of gasoline	−6722
Alternative fuel instead of gasoline	−2717

the negative image of *bombs-on-wheels*, although the focus group observation indicated that factual information regarding technical safety records of retrofit LPG cars did reach potential buyers. This is confirmed by the much lower willingness to accept for alternative fuel cars: there seems to be no reason to believe that they are more or less explosive than common LPG cars, the only observable difference is the absence of the notorious LPG-label.

Second Degree: the quadratic terms

Further specifications of the multinomial logit model have been estimated in order to include *quadratic terms* for the generic variables entering the choice sets at three levels (see table 1.9). However, for most variables we could not find any significant influence of the quadratic terms on the choice behaviour, in contrast to e.g. Ramjerdi and Rand (1999) and Bunch et al. (1993).

The only exception is the *annual cost* variable for which the coefficient of the quadratic term is significant. The estimated coefficients of the linear and the quadratic term together however result in a positive relation between annual cost and choice probability for the larger values of the annual cost, which requires more detailed investigation. By dividing the population in two clusters based on the value of B in the survey,[32] we could explain the quadratic term. By replacing the linear and the quadratic term by two linear terms, one for $B < 17500$ and another for $B \geq 17500$, the estimation result is further improved (Log Likelihood value). For the lower segment the linear coefficient was significant, whereas for the upper segment it was not. This is a more realistic result than the quadratic term specification.

However, even with the two linear terms the phenomenon remains difficult to explain. Not all respondents did specify a value for B in the first phase of the survey. The missing values in the data set have been replaced by a default value of $B = 10000$ (see section 1.5.7). This way respondents who did not state a value have been included in the lower segment in this estimation.

[32] We recall the reader here the definition of B: the amount the respondent indicated in the first phase of the survey he/she would spend in case the respondent had to buy a new car at the moment of the survey (see section 1.5.7).

Because of the interpretation difficulties that may arise when including two annual cost coefficients, we decided to stick to the original linear specification of a unique coefficient in subsequent estimations.

Interaction: the respondent interaction terms

In this section we study the further extension of the multinomial logit estimation by including *interaction variables* (or covariates).

Before we turn to estimating any model specification, we feel that we should address two issues that largely limit the scope of the estimated interaction effects.

A first issue relates to the *size of the survey population*. The survey population is $n = 209$. Including an interaction variable (e.g. emissions $\times$ age<55) comes down to estimating a separate coefficient for the corresponding generic variable (or dummy) for each population cluster defined by the definition of the interaction variable. Hence, one of both coefficients is estimated based on results by 104 respondents or less. This still seems to be acceptable as long as both clusters have more or less the same size. However, if we add a second interaction effect that clusters the population along another determinant, we get four clusters of which the smallest one can have less than 50 respondents and this may be a too small sample. This is confirmed by some tentative estimations showing that as one cluster becomes smaller this tends to result in increasing log likelihood values, a likely indication of over fitting.

We therefore limit estimations to interactions with only one respondent specific attribute, defined such that the smallest cluster for which the interaction effects are estimated still includes at least 25% of the respondents in order to avoid over fitting.

The second issue relates to the *scale factor* which is included in the coefficient estimates $\hat{\beta}$ and which reflects the variance of the stochastic utility ϵ_{jmn} (see equation (1.3)). What we want to estimate here is how the trade off between the car variables varies over segments of the population. If we allow all technology variables to interact with a given respondent specific attribute (e.g. age<55), we may end up with two coefficient vectors (one for each population cluster) which only differ in the scale parameter. This means that in such a setting the variance of the stochastic utility ϵ_{jmn} varies over the population rather than the trade off between the variables. Such an effect where scaling effects are confounded with choice variable trade-off makes coefficient estimation interpretations difficult and should be avoided. We therefore decided not to consider interactions with the cost variables: by keeping these coefficients constant over the population, we control for variation of the scale parameter σ over the population.

The character of the estimation procedure changes somewhat when interaction variables enter the model specification. Whereas the dummy and generic variables are uncorrelated[33] by design, this does not hold for the respondent specific attributes. As an example we could consider the attribute gender and head of family. The introduction of correlated variables makes the estimation procedure less straightforward: whereas in an uncorrelated setting omitting a variable should not influence the estimation results for the other variables,[34] this is not longer the case with interaction variables which are *correlated* at least in some way.

The scope of the interaction variables considered here is somehow limited. First we decided to omit respondent specific attributes that are obviously correlated to other attributes which are expected to have more explanatory power. Next, we omitted some attributes for which not all respondents provided a value, more specifically the B variable (see section 1.5.7) as well as the intended mileage: the *missing observations* would further reduce the size of the usable sample which seems a sufficient motivation not to consider them.

All these considerations limit the scope of potential estimation specifications.

We estimated specifications for different interaction variables. In table 1.13, 1.15 and 1.14 we present some of the more promising results, where interaction variables group the respondents along gender, family size or socio-demographic classification.

The first model (table 1.13) clusters the population along the *gender* variable. Two interaction effects are added to the model and both are significant. The results reveal that women care more about emissions than men do. The coefficient of the generic emissions variable is not significant any more, hence we decide that we did not find a significant preference for emissions for men. As for diesel and alternative fuel cars, these are less preferred by man. The remaining dummy for alternative cars is close to zero and insignificant, indicating that women do not have significant preferences regarding alternative cars.

If we compare the coefficients of the variables for which no interaction effect was estimated to the values obtained in the original MNL model (see table 1.11), we observe that they do not change significantly. This was expected, as the choice set where designed such that the variables are uncorrelated (see factorial design in section 1.5.7).

The specification of interaction effects along *socio-demographic classification* (table 1.14) results in a model that has a somewhat lower log-likelihood value than in the case of gender clustering. The interaction effects were defined

[33]This is not 100% correct, as some correlation has been introduced by customising the cost variables and probably also by a slightly different response rate for different values of the blocking variable. We however tested for the influence of this correlation by estimating partial multinomial logit specifications and comparing the resulting coefficients to the full multinomial logit results. This indicated that we can safely stick to the assumption of no correlation between generic variables and/or dummies.

[34]This has been verified for our survey dataset.

Table 1.13. MNL model with gender interaction effects

Variable	Unit	Coefficient	p-value
Purchase cost	1000€	−0,1224	0
Annual cost	1000€	−0,5014	0,003
Fuel cost	€/km	−10,7673	0
Available luggage space	0–1	1,0047	0
Emissions	0–1	−0,4157	0,089
Range	100km	0,2648	0
Diesel		0,7567	0
LPG		−0,7843	0
Alternative fuel		−0,0469	0,790
Fuel cell		−0,1137	0,670
Battery		−0,3597	0,180
Hybrid		0,0028	0,970
Emissions × woman	0–1	−0,8502	0
(diesel | alternative) × man		−0,5239	0
Log likelihood		−1734,6794	

Table 1.14. MNL model with social class interaction effects

Variable	Unit	Coefficient	p-value
Purchase cost	1000€	−0,1239	0
Annual cost	1000€	−0,5036	0,003
Fuel cost	€/km	−10,7551	0
Available luggage space	0–1	0,4077	0,034
Emissions	0–1	−0,8680	0
Range	100km	0,2648	0
Diesel		0,4646	0
LPG		−0,8154	0
Alternative fuel		−0,3199	0,048
Fuel cell		−0,1405	0,598
Battery		−0,1730	0,553
Hybrid		0,0031	0,967
Battery × class<5		−0,4616	0,041
Luggage × class<5	0–1	1,1455	0
Log likelihood		−1736,1368	

based on the socio-demographic classification of the respondent: the four lowest classes of the ESOMAR standard (see section 1.5.4) were included in the interaction, this corresponds to 59% of the respondents.

We observe that the lower classes care more about luggage space, and dislike battery cars more than the higher classes do. Both effects are significant, but it is unclear if they tell us much.

A third interaction effects model studies interaction with *family size* and is presented in table 1.15.

From the table 1.15 we observe that respondents from larger families care more about emissions and value luggage space more positively. Respondents from smaller families tend to be more negative towards diesel, LPG or alternative fuel vehicles.

The gender based interaction specification has the best estimation statistic (log likelihood), we hence decide to stick to this setup in further estimations.

In past studies, household income proved to have a significant influence on car technology choice. However, it is also a variable that is very difficult to measure in a survey. To avoid running the risk of failing to measure household income, we made use of a standardised demographic classification by ESOMAR (see section 1.5.4). For each ESOMAR class, the average income is determined based on population statistics. We have tested different modelling specifications for the income variable specified as a continuous variable (not discrete) interacting with dummy technology variables, however no significant influence on purchase behaviour was found. Probably the size of the survey is too small to provide enough variance across respondents.

Table 1.15. MNL model with family size interaction effects

Variable	Unit	Coefficient	p-value
Purchase cost	1000€	−0,1235	0
Annual cost	1000€	−0,4988	0,003
Fuel cost	€/km	−10,7843	0
Available luggage space	0–1	0,7549	0,034
Emissions	0–1	−0,5964	0,013
Range	100km	0,2635	0
Diesel		0,8942	0
LPG		−0,3931	0,049
Alternative fuel		−0,0979	0,605
Fuel cell		−0,1107	0,679
Battery		−0,3439	0,201
Hybrid		0,0069	0,927
Emissions × family size>3	0–1	−0,6772	0
Luggage × family size>3	0–1	0,6619	0,028
(diesel | LPG | alternative) × family size<4		−0,6251	0
Log likelihood		−1738,4169	

1.6.2. Nested logit

The next step in model estimation is to switch to a nested logit specification. This allows for correlation in unobserved preferences (stochastic utility) for different alternatives in the same choice set.

In estimating nested logit specifications,[35] we tested for several nesting structures but only one was found to result in a significant better modelling structure (χ-square test on log-likelihood with one degree of freedom): all internal combustion engine technologies in a nest (see figure 1.1). The model coefficients are shown in table 1.16.

Comparing our modelling results to past research, we note that the nesting structure identified by Ramjerdi and Rand (1999) and Bunch et al. (1993) is similar to what we observed.

The further interpretation of the model coefficients will not be discussed here, as most conclusions on the significance, signs and WTP-values observed in the multinomial logit model still hold. Only alternative-specific dummies do show some changes.

The log-sum coefficient (see appendix A) is a measure for the correlation in unobserved preferences (or stochastic utility) for the alternatives in the nest. We should however stress here that in the nested logit specification, different choices are considered as independent. Correlation hence concerns only alternatives in the same choice set. This is a drawback as it seems realistic to assume that correlation in preferences is much stronger at the level of the respondent rather than at the choice set level. To overcome this limitation of the nested logit model, we will continue our analysis with the mixed logit specification.

[35] For nested logit estimation, the nlogitrum command in Stata was used to ensure consistency with random utility maximisation (Heiss, 2002)

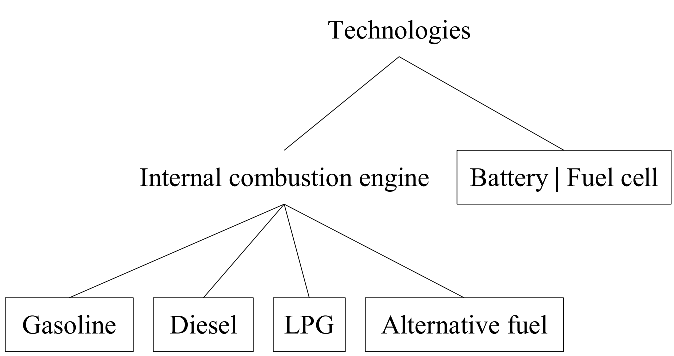


Figure 1.1. Nesting structure

Table 1.16. Nested logit choice model

Variable	Unit	Coefficient	p-value
Purchase cost	1000€	−0,0971	0
Annual cost	1000€	−0,3955	0,004
Fuel cost	€/km	−8,3326	0
Available luggage space	0–1	0,8824	0
Emissions	0–1	−0,2848	0,125
Range	100km	0,2270	0
Diesel	dummy	0,5351	0
LPG	dummy	−0,4879	0,002
Alternative fuel	dummy	−0,0367	0,775
Fuel cell	dummy	−0,3489	0,775
Battery	dummy	−0,5974	0,009
Hybrid	dummy	0,0090	0,869
Emissions × woman	interaction	−0,6589	0
(diesel | alternative) × man	interaction	−0,3653	0,001
λ (log-sum)		0,7058	0
Log likelihood		−1731,8291	

1.6.3. Mixed logit

The major enhancement of the mixed logit specification over NL or MNL for the analysis of our stated preference data set is that allows to account for the repeated choice character: every respondent answered six choice sets.[36] The structure of the data is illustrated in figure 1.2.

The different mixed logit models described in this text have all been estimated making use of the *gllamm* command[37] in Stata.

We recall equation (1.5) for the utility U_{jmn} in a mixed logit setting, allowing for distributed coefficient values: α here contains the mean value of the coefficient, whereas the variance is captured by the error terms μ_n (which in turn have mean zero).

The estimation of mixed logit model specifications is computationally more demanding than the nested logit or multinomial logit, due to the absence of a closed form expression for the choice probabilities (see appendix A). This

[36]There are various ways to address issues in estimation related to repeated choices in the observations. One way is to allow for correlation structures by specifying the deterministic part of utility accordingly. This can be done by introducing covariates (choice variables that interact with respondent specific attributes) as demonstrated in section 1.6.1. An alternative would be to estimate respondent-specific coefficients β_n provided that enough choice information is available at the respondent level (barring a blocked setup as applied in our survey). A more generic way is to allow for correlation in unobserved choice preferences (represented by random utility in discrete choice models). The multinomial and nested logit specification of random utility do not allow for the appropriate correlation structures by definition, therefore the application of a mixed logit specification is required.

[37]Rabe-Hesketh (2005); applications to discrete choice data are discussed in Skrondal and Rabe-Hesketh (2003, 2004)

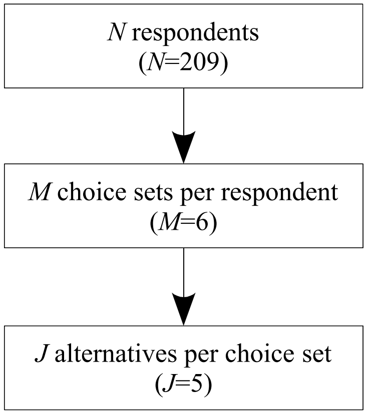


Figure 1.2. Structure of stated preference data set

precludes the estimation of a mixed logit specification including several error terms μ_n.[38]

The approach we applied is to look first at error terms μ_n for the dummies and generic variables one by one.[39]. Such an approach may seem to be rather rough, but we should remind here that the levels of the variables in the choice sets are uncorrelated as they have been fixed using an orthogonal plan. The estimation of the different mixed logit specifications is provided in table 1.17

We should add here that the approach applied misses out on covariance, however in most past research error terms μ_n have been specified as independent. We will come back to the issue of covariance when we study selected combinations of error terms.

The *variance* of the error term μ_n of the dummy variable for gasoline, diesel, LPG, alternative fuel, fuel cell and battery is significant and provides for a considerable improvement of the model fit. The improvement in log likelihood value (compared to the MNL specification with interaction variables) is of a much larger order of magnitude than what we could attain with the nested logit specification, indicating that by modelling correlation in stochastic utility at the respondent level rather than at the choice set level results in a more realistic modelling of the choice behaviour.

If we look into the *mean* coefficient values α (not reported here), we observe that these are generally larger in the mixed logit estimations compared to the multinomial logit specification. This is a scaling effect: larger α values

[38]There are some possibilities to speed up model estimation. First the combination of gllamm and Stata version 7 is not optimised, later versions should do the job in less time. Alternatively other software may allow for shorter estimation times, e.g. the open source application Amlet (Bastin, 2004) which implements a different and probably more efficient numerical approach. Finally as faster computers become available estimation speed should go up as well—estimations discussed here were ran on computers with CPU speed varying from 0,4 to 1,5 GHz.

[39]This comes down to fixing the variance of all but one error terms μ_n to zero.

Table 1.17. Mixed logit specifications with one error term

Error term μ_n	Variance of μ_n		Log-Likelihood	
	value	p-value	value	p-value
Gasoline	5,09	0,000	−1614,1	0,000
Diesel	6,76	0,000	−1549,3	0,000
LPG	1,84	0,001	−1717,7	0,000
Alternative fuel	1,45	0,001	−1718,0	0,000
Fuel cell	6,59	0,000	−1687,4	0,000
Battery	7,00	0,001	−1694,2	0,000
Hybrid	0,11	0,381	−1734,2	0,320
Purchase cost	0,20	0,711	−1734,6	0,698
Annual cost	$1{,}00 \cdot 10^{-12}$	1,000	−1734,7	1,000
Fuel cost	0,01	0,994	−1734,7	1,000
Range	0,51	0,000	−1668,5	0,000
Emissions	9,73	0,000	−1548,4	0,000
Luggage	5,63	0,000	−1702,7	0,000

indicate a smaller variance on the i.i.d. ϵ_{nj} term: this variance is now captured by the error term μ_n. This is in line with the observation that the larger the improvement in log-likelihood, the larger the scale effect: a smaller variance in ϵ_{nj} generally indicates that the choice process is better captured by the other utility terms $(\alpha' x_{jmn} + \mu_n' x_{jmn})$.

The absolute value of the variance of the gasoline, diesel, fuel cell and battery error term μ_n does not differ significantly. The value itself is rather large compared to the order of magnitude of the corresponding dummy coefficients α. This indicates that there is a large variance in fuel-based preferences over the respondents: some respondents apparently would buy a diesel car without really considering the other alternatives. It is somehow in line with the focus group observation that car buyers link fuel to a lot of other car attributes (like driving behaviour) and that the choice for a fuel may be inspired by e.g. family tradition.[40]

In a comparable way the value of the variance for the LPG and alternative fuel dummy error term μ_n do not differ significantly, but the value itself is much smaller than for the other technology specific dummies.

If we look into the mixed logit model specification with an error term μ_n on the dummy for hybrids, we observe that the variance of this error term does not differ significantly from zero. Again we can not identify any

[40] An issue that is not considered here is the inclusion in the model of a decision variable that represents current vehicle ownership. Literature on reference dependence (Kahneman and Tversky, 1979; List, 2004) suggests that respondents may have status quo bias. In our model estimations the technology dummies account for the influence of current (aggregate) technology shares on technology choice, without however making this relationship explicit at the level of the individual respondent.

significant preference for the hybrid car variable. As the values of this variable in the choice sets is uncorrelated with the values of the other attributes, we can draw the conclusion that we obtain a result that is identical to what we would have obtained if we did not include the variable in the choice sets (but did include it in the estimation procedure).

The model estimations where an error term is added to the coefficients of the cost variables do not result in a significant improvement of the model fit statistic (LL). At first sight this is in line with our assumption that we should keep the coefficient cost variable fixed over all respondents. However, there is an additional consideration to be made here. The distribution of the error term in the models presented in table 1.17 is normal, the gllamm procedure in Stata not allowing for a different specification. For the dummy variables this seems not problematic, as we did not expect a specific sign for their coefficient value. For cost variables this expectation does not hold: a negative coefficient value is not acceptable. In such case a log-normal distribution would be more appropriate, but lacking this possibility in the software solution used in this study we decided to limit the analysis here.[41]

As for the remaining generic variables (luggage space, emissions and range) the addition of an error μ_n term does result in a significant improvement of the model fit. Apparently the default of a normally distributed error term did allow here for a model improvement, although the same consideration as for cost variables that a change in sign seems unrealistic applies here. Especially for emissions the improvement in model fit is rather large.

Now that we have discussed a one-by-one estimation of error terms μ_n, we will focus somewhat more on selected combinations of dummies in order to better understand the correlation in the stochastic utility. We will specify error terms μ_n for two variables which are not independent (the error terms). This results in the estimation of three coefficients: the variance of the two error terms and the covariance.

In a first exercise we go back to the observation by Batley et al. (2003) that in their survey the respondents could clearly identify the (unlabelled) alternative car through the survey design. In our setup we analogously wonder whether a *fifth car* effect plays for the fuel cell and battery car. Considered the strong fuel related preferences, it seems realistic to expect that respondents identified the fuel cell or battery car as the fifth car in the choice sets and hence expect them to be somehow similar.[42]

To study this behaviour, we define two error components μ_n, one for battery and one for fuel cell, and allow for covariance. The resulting model is presented as Model A in table 1.18.

[41]Other software solutions such as Amlet (Bastin, 2004) do provide for the possibility of log-normal distributed error terms

[42]We recall here that as opposed to gasoline, diesel, alternative fuel and LPG technologies which entered all choice sets, the fuel cell and battery car technologies alternated and each entered only half of the choice sets.

Table 1.18. Mixed logit model for battery and fuel cell technologies

		Model A		Model B	
Variable	Unit	Coefficient	p-value	Coefficient	p-value
Mean value α					
Purchase cost	1000€	−0,1454	0	−0,1453	0
Annual cost	1000€	−0,5854	0,001	−0,5878	0,001
Fuel cost	€/km	−12,5772	0	−12,5759	0
Available luggage space	0–1	1,3461	0	1,3428	0
Emissions	0–1	−0,4985	0,065	−0,4953	0,065
Range	100km	0,3530	0	0,3528	0
Diesel		0,7752	0	0,7752	0
LPG		−0,6403	0	−0,6387	0
Alternative fuel		0,1356	0,455	0,1368	0,450
Fuel cell		−0,9363	0,017	−0,9673	0,008
Battery		−1,3403	0,001	−1,4399	0
Hybrid		−0,0219	0,780	−0,0227	771
Emissions × woman		−0,8349	0	−0,8351	0
(diesel | alternative) × man		−0,5458	0	−0,5461	0
Variance of error term μ_n					
Fuel cell		6,6958	0		
Battery		6,3234	0		
(fuel cell | battery)				6,7274	0
Correlation of error terms μ_n					
		0,9864	0,001		
Log likelihood		−1602,0355		−1601,6083	

We observe a correlation of 98,6%, which means that the variation over respondents in preferences for fuel cell and battery technologies is practically fully correlated. Technically this correlation could be attributed to the battery and fuel cell cars not being equipped with an internal combustion engine as opposed to the other technologies (this was indicated as such in the survey). Given the strong fuel related preferences for the internal combustion technologies, we however attribute (at least part of) the correlation to the *fifth car* effect induced by the survey design.[43]

The near-perfect correlation together with the level of the variance of both error terms being of the same order of magnitude motivated us to re-estimate the model with one error term μ_n for all non-ice[44] technologies. The

[43]The choice sets in the survey all include five cars. Whereas all choice sets include a diesel, gasoline, LPG and CNG car, the fifth car alternated between electrical battery and fuel cell technology. With the *fifth car* effect we indicate the possible perception by the respondent that electrical battery and fuel cell technology may have something in common as they alternate in the choice set as opposed to the other technologies.

[44]Internal combustion engine

estimation results of this specification are presented as Model B in table 1.18. As expected this results in a model that behaves roughly identical to Model A. The improvement in log-likelihood however seems to be an aberration: this is technically impossible and should hence be attributed to the numerical approach algorithm implemented by gllamm. It provides an indication of the accuracy of the numerical calculation.[45] Assuming that both models have about the same log likelihood value, we can draw the conclusion that no improvement is attained by introducing two estimation variables and hence the simpler model does the job.

A second exercise studies the correlation in preferences for conventional diesel and gasoline technologies. We again define two error components and allow for covariance in the estimation procedure. The resulting model is presented as Model A in table 1.19.

We observe a correlation of 43% for the variance in preferences for diesel and gasoline alternatives over technologies. The variance itself does not differ significantly between both fuels. The increase in log-likelihood is considerable—this is the best model fit we obtained so far.

To check for the impact of the correlation level on the model fit, we estimated a similar model where both error terms for diesel and gasoline are defined independently (zero correlation) and their variance is set equal. This model is presented as Model B in table 1.19. Comparing the log-likelihood values we decide that Model A is significantly better (at $p \leq 0{,}05$ for two degrees of freedom) than Model B—however, we should here recall the inaccuracy of the numerical approach which may influence this judgement on significance as the increase in log-likelihood is not large.

We finally revisit the implicit *willingness-to-pay* for selected choice variables and now calculate these figures based on Model A from table 1.19. The resulting values are presented in table 1.20.

We observe willingness-to-pay values for the generic variables which are generally somewhat smaller (in absolute value) than our results based on a multinomial logit estimation (see table 1.12). Values for the dummy variables are slightly different, although this can be explained by the interaction terms which were not considered in the multinomial logit results. We should here recall that the values for diesel are average values, as for this variable an error term μ_n was added in the mixed logit estimation.

1.7. Conclusions

In this chapter we studied the design and implementation of a private car technology choice survey. The stated preference data collected allowed for the

[45] It is possible to rise the number of integration points in gllamm. However, calculation time is roughly proportional to n^M where n is the number of integration points and M is the number of random effects, enhancing the accuracy thus results in fast-increasing time requirements.

Table 1.19. Mixed logit model for gasoline and diesel technologies

Variable	Unit	Model A		Model B	
		Coefficient	p-value	Coefficient	p-value
Mean value α					
Purchase cost	1000€	−0,1851	0	−0,1846	0
Annual cost	1000€	−0,8029	0	−0,8018	0
Fuel cost	€/km	−15,8720	0	−15,9077	0
Available luggage space	0–1	1,1743	0	1,1584	0
Emissions	0–1	−0,3463	0,211	−0,3368	0,220
Range	100km	0,3154	0	0,3098	0
Diesel		1,0528	0	1,3082	0
LPG		−0,4094	0,156	−0,0525	0,854
Alternative fuel		0,4468	0,140	0,8083	0,007
Fuel cell		0,3411	0,351	0,6949	0,055
Battery		0,0408	0,911	0,3982	0,271
Hybrid		0,0354	0,708	0,0342	0,719
Emissions × woman		−1,2162	0	−1,2198	0
(diesel | alternative) × man		−0,6917	0,001	−0,7045	0,002
Variance of error term μ_n					
Diesel		7,9736	0	6,4510	0
Gasoline		6,0151	0	6,4510	0
Correlation of error terms μ_n					
		0,4262	0,005	0	
Log likelihood		−1440,327		−1445,9411	

Table 1.20. WTP in mixed logit choice model (in €)

technology change	WTP in €
reduction in trunk space of 10% (compared to diesel/gasoline car)	−634
reduction in emissions of 10% (compared to gasoline car)	657
100km shorter range	−1704

design and estimation of a range of discrete choice models for Flanders to analyse preferences for alternative technologies.

The methodology applied allowed to estimate significant coefficients for all generic variables regardless the limited sample size. This includes a variable for emissions, indicating a willingness to pay for cleaner cars.

For hybrid cars, no significant preferences could be detected.

Mixed logit specifications are more flexible and allow to account for the repeated choice character of our data set. Hence a better fit was obtained than with multinomial or nested multinomial specifications.

CHAPTER 2

Simulating the market for alternative cars

2.1. Introduction

The research and development of a broad range of alternative fuels and private car technologies has received much attention in recent research (overviews of alternative fuels and technologies are provided by Arcoumanis, 2000; Burgwal et al., 2001; IEA, 1999; Verbeiren et al., 2003). While some technologies are still at an experimental stage (e.g. fuel cell), others have matured and are being introduced on the market (e.g. hybrid power trains).

The environmental performances of alternative technologies are generally better than conventional cars. This raises the question if and how the authorities should act in order to increase the market share of the new technologies. Different policy options exist, including subsidies or taxes, the (partial) banning of the more polluting conventional technologies etc. Hence the need emerges for a flexible simulation tool that allows for an assessment of the impact of different policy measures on consumer behaviour. In this chapter we discuss the design of a model for the simulation of the preferences for private car technologies in Belgium. The scope of the model includes both conventional and alternative car technologies.

Discrete choice theory (Anderson et al., 1992; Ben-Akiva and Lerman, 1985; K. Train, 1986/1990; K. E. Train, 2003) provides a modelling framework for the analysis and simulation of private car technology choice. As discussed in chapter 1, the analysis of choice preferences for alternative technologies commonly uses stated preference data. The repeated choice character of such a stated preference data set requires a mixed logit specification in model estimation, a finding in chapter 1 that is in line with e.g. Batley et al. (2003).

The advent of more powerful computers has removed the barrier of computational demands of the *mixed logit* specification in model estimation, resulting in several applications of the mixed logit model in analysis of the choice for alternative technologies (e.g. Batley et al., 2003; Brownstone and Train, 1999). In simulation however the picture is somewhat different. The absence of a closed expression for the choice probabilities makes the mixed logit framework inflexible compared to the multinomial and nested multinomial logit model, especially if the technology choice model is to be included in a larger transport activity model. Moreover, in simulation there is no need for a repeated choice setting, making the choice for a mixed logit specification less obvious. Recent applications in technology choice simulation show that the implementation of *nested logit* specifications is common, examples include COWI A/S (2002) and De Borger and Mayeres (2004).[1]

The literature provides examples of *mixed nested logit* models. K. E. Train (2003) mentions the possibility of estimating a mixed logit model that provides correlation-substitution patterns similar to those of a nested logit model. An application can be found in Batley et al. (2003) where the mixed logit model is used to re-estimate and extend a nested logit specification. There seems not to be an implementation of the mixed nested logit approach in a simulation application as of writing this chapter.

A next issue in simulation is the use of stated preference data for model estimation. Stated preference data have many benefits over revealed preference data, the latter typically showing heavy correlation in choice variables (Brownstone et al., 2000). However, the major drawback of stated preference data is the absence of any guarantee that they reflect real world behaviour. This problem raises the question on the possibilities to combine best of both worlds. Joint revealed and stated preference estimation procedures have been discussed by e.g. Ben-Akiva and Morikawa (1997) for multinomial logit models and Brownstone et al. (2000) for mixed logit models.

In our approach to the topic we will explore the possibilities to combine mixed logit in estimation and nested logit in simulation. The stated preference data set collected by the survey discussed in chapter 1 will serve as a base for model estimation.[2]

We will specify a mixed nested logit choice model accounting for the

[1] It should be noted that the examples referenced here simulate the choice for conventional technologies rather than alternative ones. For the analysis of preferences for conventional technologies the use of a revealed preference data set is common. The absence of the repeated choice characteristic makes the choice for mixed logit specifications less straightforward, in literature we commonly find nested logit specifications in this setting (e.g. COWI A/S, 2002; De Jong, 1996; Verboven, 1996).

[2] The geographical scope of the simulation model developed in this chapter is the Belgian car market, whereas the dataset collected in chapter 1 only cover technology choice observations by Flemish car users. The choice for the scope of the simulation model is motivated by the data requirements for the calibration of the TREMOVE vehicle stock model which are more easily (and consistently) met at the Belgian level rather than the level of the Flemish Region. The implicit assumption in this chapter is hence that our stated preference technology choice dataset is representative for the entire Belgian market.

repeated choice setting and using the insights on correlation-substitution patterns identified in our analysis in chapter 1. Next we show how the estimation results can be used to design an efficient and flexible nested logit simulation tool. This is an innovating application of the nested mixed logit model.

The mixed nested logit specification provides a modelling framework that allows for the repeated choice character of the survey data set. Additionally, we show how we can use the mixed nested logit model in estimation to identify correlation-substitution patterns that are more complex than in a pure nested logit specification. Using this information allows to design a nested logit simulation tool that models an extended structure of correlation in preferences for alternatives.

In a second step we study the integration of the stated preference simulation model with a revealed preference choice model for conventional technologies.[3] We show how the approach discussed in literature can be extended to allow for the integration of two nested logit models.

The joint revealed and stated preference estimation of discrete choice models combines the strong points of both approaches. We discuss how this methodology can be extended to nested logit and show how correlation-substitution patterns identified in both data sets can be combined in the integrated model.

Our final technology choice model covers a rather extended range of alternative as well as conventional technologies. Its nested logit specification allows for flexible application and integration in the framework of the TREMOVE 2 transportation model. In chapter 3 we will discuss a simulation (including a welfare assessment) of the environmental potential of the alternative technologies.

The structure of this chapter is as follows. In a first section we provide a concise introduction on the topic of discrete choice theory.

A subsequent section focuses on the design of a flexible choice simulation tool based on stated preference data (survey chapter 1). The section compares the nested logit to the mixed nested logit model and in a next step enhances the model specification to account for the repeated choice setting. In a final step it concludes with the design of a nested logit simulation tool based on the mixed nested logit estimation results.

In the following section we provide a methodology to integrate our stated preference model with the TREMOVE 2 revealed preference model. In a first step the revealed preference model is introduced and we show how we can compare it to our stated preference based simulation tool (developed in the previous section). In a second step both nested logit simulation models are integrated.

[3]The revealed preference choice model used in this chapter is based on TREMOVE 2 (G. De Ceuster et al., 2005).

In a final section we draw conclusions.

2.2. Discrete choice

Discrete choice theory provides a broad range of modelling frameworks. An extended introduction on the topic is provided in appendix A. An in depth discussion on discrete choice theory can be found in Anderson et al. (1992); Ben-Akiva and Lerman (1985); K. Train (1986/1990); K. E. Train (2003).

The consumer who considers the purchase of a car faces a discrete choice problem. Discrete choice theory models the probability that a consumer n chooses a given alternative j in choice situation[4] m as a function of the *random utility* U_{jmn} of the alternatives, expressed as:

$$U_{jmn} = V_{jmn} + \epsilon_{jmn} \tag{2.1}$$

where:

- V_{jmn}: the *deterministic part* of the utility for alternative j as obtained by consumer n in choice situation m—we will in this section assume that V_{jmn} is linear in parameters: $V_{jmn} = \beta' x_{jmn}$ with β a vector of coefficients and x_{jmn} a vector of decision variables relating to consumer n and alternative j in choice situation m;
- ϵ_{jmn}: the *stochastic part*.

The consumer then chooses the alternative with the highest utility (utility maximisation).

The *multinomial logit* model (MNL) assumes a Gumbel distribution with variance $\sigma^2\pi^2/6$ for the stochastic utility ϵ_{jmn}. As we can see from expression (2.1), any linear transformation does not affect the choice probabilities. This makes it impossible to identify the value of the scale parameter σ of the stochastic part separately from the coefficients β of the deterministic part. In estimation the utility U_{jmn} is scaled by a factor $1/\sigma$ which normalises the variance of the stochastic part to $\pi^2/6$. The estimated coefficients $\hat{\beta}$ include the scale parameter σ of the stochastic utility:

$$\hat{\beta} = \beta/\sigma \tag{2.2}$$

Appendix A discusses how the scale parameter of two independent model estimations can be compared using the ratio of their respective coefficient estimates $\hat{\beta}$.

The *nested multinomial logit* model (NL) extends the multinomial logit specification by allowing for correlation in unobserved preferences (stochastic utility) for a subset of alternatives. A partition structure defined by the

[4]The index for choice situation m is introduced here to account for the repeated choice character of survey data.

researcher groups the alternatives in subdivisions or nests $S_1 \ldots S_K$. The utility U_{jmn} of alternative j in nest k can be expressed as:

$$U_{jmn} = V_{jmn} + \underbrace{\eta_{kmn} + \epsilon_{jmn}}_{\text{stochastic utility}} \tag{2.3}$$

with:

- V_{jmn} the deterministic (observed) utility of alternative j;
- ϵ_{jmn} independent for all alternatives j, choice situations m and respondents n;
- η_{kmn} independent for all nests k, choice situations m and respondents n;
- ϵ_{jmn} iid Gumbel distributed with scale parameter λ_k;[5]
- η_{kmn} distributed so that $\max_{j \in S_k}(U_{jmn})$ is Gumbel distributed with scale parameter σ normalised to unity.

For each nest k the parameter λ_k ($0 \leq \lambda_k \leq 1$) is a measure for the correlation between the alternatives in nest k, with values closer to unity indicating less correlation.

The choice probability P_{jmn} of alternative j (in nest k) in choice situation m by respondent n can in a nested logit specification be expressed as:

$$P_{jmn} = \frac{e^{\lambda_k I_{kmn}}}{\sum_{i=1}^{K} e^{\lambda_i I_{imn}}} \frac{e^{\hat{\beta}' x_{jmn}/\lambda_k}}{e^{I_{kmn}}} \tag{2.4}$$

with I_{kmn} the inclusive value of nest k, defined as:

$$I_{kmn} = \ln \sum_{j \in S_k} e^{V_{jmn}/\lambda_k} \tag{2.5}$$

The *mixed logit* model (ML) is a further extension to the multinomial logit that provides a very flexible modelling framework. It defines the utility U_{jmn} of alternative j in choice situation m by consumer n as:[6]

$$U_{jmn} = \alpha' x_{jmn} + \underbrace{\mu_{jmn}{}' z_{jmn} + \epsilon_{jmn}}_{\text{stochastic utility}} \tag{2.6}$$

with

- α a vector of fixed coefficients
- μ_{jmn} a vector of random terms with mean zero and probability distribution $f(\mu_{jmn})$, any distribution can be used (independence over j, m or n is *not* a necessary condition)

[5] In fact λ_k is defined as σ_k/σ with σ the scale parameter of $\max_{j \in S_k}(U_{jmn})$ (here normalised to unity) and σ_k the scale parameter of ϵ_{jmn}.

[6] We limit here to the case of linearity in choice variables in order to keep the notations simple.

- x_{jmn} and z_{jmn} vectors of observed variables
- ϵ_{jmn} i.i.d. Gumbel distributed with scale parameter σ normalised to unity (independent over all alternatives j, choice situations m and respondents n)

The vector z_{jmn} may or may not include the same variables as x_{jmn}, depending on the correlation pattern studied.

2.3. Stated preference model estimation

In this section we will discuss the design and estimation of a simulation tool based on the stated preference data set we collected in the survey discussed in chapter 1. The structure of the data set is presented in figure 2.1.

We will start with a simple nested logit model. In the second subsection we have a closer look to the mixed nested logit model and explore a methodology that allows us to improve our nested logit simulation tool using mixed logit estimations. In a first step we use the mixed nested logit specification without accounting for the repeated choice character of the data set in order to allow for a comparison with the pure nested logit estimation of the first subsection. In a next step we upgrade the mixed nested logit specification in order to account for the repeated choice setting and to refine the substitution-correlation patterns. The last subsection discusses the technological scope of our simulation tool.

2.3.1. Nested logit

A nested logit model has been estimated in chapter 1. To allow for an integration in the TREMOVE modelling framework (see section 2.4) we will

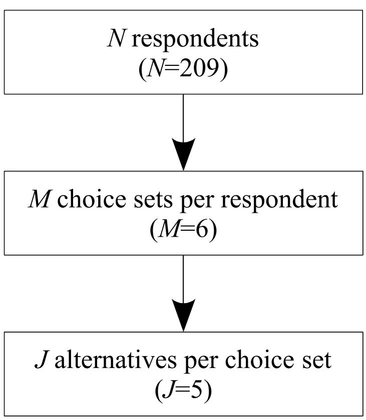


Figure 2.1. Structure of stated preference data set

however propose two changes in the specification. The first change is to drop the interaction variables, as they seem of no direct use in our application (see chapter 3 and beyond).[7]

A second change is the introduction of a single composite user cost variable. The lifetime cost per kilometre of alternative j aggregates the three cost based variables:[8]

$$LFC_{jmn} = \frac{PC_{jmn}\frac{(1+i)^y}{(1+i)^y-1}i + AC_{jmn}}{d_n} + FC_{jmn} \tag{2.7}$$

with:

- PC_{jmn} the purchase cost of alternative j in choice set m of respondent n;
- AC_{jmn} the annual cost of alternative j in choice set m of respondent n;
- FC_{jmn} the per kilometre fuel cost of alternative j in choice set m of respondent n;
- d_n the expected annual mileage: in the second phase of the survey (see chapter 1) the respondents were asked their intended mileage d_n after they revealed their technology choices. Some missing values could be replaced by the value the respondent provided in the first phase as their actual mileage. For the handful respondents where both values were missing, a default mileage value of 20 206 km was used;[9]
- y an expected vehicle lifetime of 9,5 years, a value based on the TREMOVE 2 model for the Belgian car market;[10]
- i a discount rate which has been fixed to 4% (value used in TREMOVE).[11]

[7] In the TREMOVE 2 framework such interaction variables may be useful to explain differences in choice behaviour between the different EU-countries using demographic differences as an input. In our applications the focus will be limited to Belgium. In the estimation of interaction variables in chapter 1 we noted that the size of our data set limits its potential for the estimation of interaction variables.

[8] The definition applied here follows the specification of the TREMOVE 2 model. This definition allows an integration with the TREMOVE 2 revealed preference choice model in section 2.4.

[9] This default value is based on TRENDS project data (Samaras et al., 2002), and was found to be close to the sample average. An alternative approach would have been to eliminate from the estimation dataset the choices made by respondents for which no specific mileage value is available.

[10] The expected lifetime values in TREMOVE 2 are calculated on stock composition parameters provided by the TRENDS project (Samaras et al., 2002). In this chapter we use data issued from TRENDS on 29 December 2003.

[11] There has been discussion in the literature as to the rationality of the consumer in trading off current costs for future expenses. A 2006 review of the TREMOVE model (Skinner et al., 2006) discusses consumer myopia for lifetime costs, and indicates that discount ranges have been found to range between 0 and 41% (based on the review by K. Train, 1985). Most of the evidence for this range dates from the early 1980s, and higher values for the discount rate can probably in part be attributed to higher inflation rates prevailing in that monetary era. More recently Verboven (2002a) reported a discount rate of 11,5% for the period 1990 to 1994 based on the analysis of revealed preference car purchase records. This finding is in line with the suggested value of 4% (in constant prices) if we take into account interest rates on capital markets in the early 90s.

After substituting the new lifetime cost variable for the original three cost variables, we re-estimate the nested logit model (nesting structure see figure 2.2)[12] and present the result in table 2.1.

Throughout this section we will use the p-value as a measure of significance in the different models discussed. The p-value of a coefficient estimation $\hat{\beta}$ indicates the probability that, given that the null hypothesis (true coefficients are zero) is true, the coefficients β assume a more extreme value than the observed (estimated) $\hat{\beta}$. As a rule to decide on significance, we will use in this chapter $p \leq 0{,}05$. Although any threshold value for significance is entirely arbitrary, insights gained in simulations (see chapter 1) resulted in the selected level.

The 95% confidence interval (see table 2.1) provides an indication of the influence of the sample size (209 respondents) on the estimation results: it indicates a range around the estimated value in which the real coefficient (of the whole population) is situated with a probability of 95% for a random sample. The confidence interval is linked with the p-value: a 95% confidence interval that has 0 as delimiting value will result in a p-value of 5%.

Table 2.2 provides a comparison of the model (table 2.1) to the corresponding nested logit model estimated in chapter 1. We observe a log likelihood value which is somewhat larger (absolute value) than what we obtained by the more extended specification. The overall difference is not large although, based on the test statistic (χ square with 4 degrees of freedom), the extended model still performs significantly better.

This model is about the best we can get in a pure nested logit specification. However, we did not account for the repeated choice character of the survey data set in estimating the model. In chapter 1 we showed that by accounting for this (using a mixed logit), the model fit improved dramatically indicating

[12] We have represented a nest *elc* on the figure. This is a single member nest, its use will be in the nested mixed logit discussion in section 2.3.2.

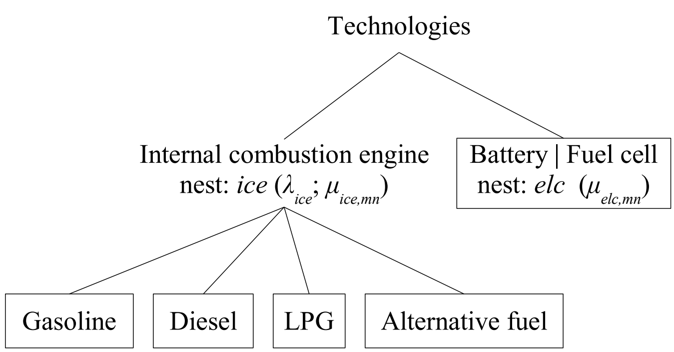


Figure 2.2. Nesting structure

Table 2.1. Estimation of nested logit choice model for simulation

Variable	Unit	coefficient	p-value	95% conf. interval	
				low	high
Lifetime cost	€/km	−5,399	0	−7,3715	−3,4266
Luggage space	0–1	0,7443	0	0,4497	1,0389
Emissions	0–1	−0,5624	0,001	−0,9045	−0,2202
Range	100 km	0,2081	0	0,1333	0,2829
Diesel		0,2902	0	0,1522	0,4283
LPG		−0,4378	0,003	−0,7311	−0,1444
Alternative fuel		−0,1273	0,259	−0,3486	0,0940
Fuel cell		−0,4670	0,030	−0,8893	−0,0447
Battery		−0,7206	0,001	−1,1479	−0,2932
Hybrid		−0,01257	0,793	−0,10626	0,08112
Log likelihood		−1763,3508			

Table 2.2. Comparison of simulation logit choice model to results from chapter 1

		NL chapter 1		Simulation NL	
Variable	Unit	coefficient	p-value	coefficient	p-value
Purchase cost	1000 €	−0,0971	0		
Annual cost	1000 €	−0,3955	0,004		
Fuel cost	€/km	−8,3326	0		
Lifetime cost	€/km			−5,399	0
Luggage space	0–1	0,8824	0	0,7443	0
Emissions	0–1	−0,2848	0,125	−0,5624	0,001
Range	100 km	0,2270	0	0,2081	0
Diesel		0,5351	0	0,2902	0
LPG		−0,4879	0,002	−0,4378	0,003
Alternative fuel		−0,0367	0,775	−0,1273	0,259
Fuel cell		−0,3489	0,775	−0,4670	0,030
Battery		−0,5974	0,009	−0,7206	0,001
Hybrid		0,0090	0,869	−0,0126	0,873
Emis. $\times$ woman		−0,6589	0		
(diesel $\mid$ alt.) $\times$ man		−0,3653	0,001		
λ_{ice} (log-sum)		0,7058	0	0,6204	0
Log likelihood		−1731,8291		−1763,3508	

that a model specification that cannot account for repeated choice should be avoided if possible. In section 2.3.3 we will explore an approach to account for repeated choice in estimation without having to use the computationally demanding mixed logit framework in simulation.

2.3.2. Nested logit & Mixed logit: the link

In this section we discuss whether and how we can use the mixed logit framework for the design of a tool that allows for fast simulations.

We start from the expression for the perceived utility U_{jmn} of alternative j in choice situation m faced by respondent n in the mixed logit model specification (see equation (2.6)):

$$U_{jmn} = \alpha' x_{jmn} + \mu_{jmn}' z_{jmn} + \epsilon_{jmn} \tag{2.8}$$

with:

- α a vector of fixed coefficients
- μ_{jmn} a vector of random terms with mean zero and probability distribution $f(\mu_{jmn})$
- x_{jmn} and z_{jmn} vectors of observed variables
- ϵ_{jmn} i.i.d. Gumbel distributed with scale parameter σ normalised to unity (independent over all alternatives j, choice situations m and respondents n)

As noted by K. E. Train (2003) and Batley et al. (2003), it is possible to define a mixed logit specification that provides correlation-substitution patterns that are similar to those of a nested logit by defining z_{jmn} appropriately. The corresponding mixed nested logit specification for the nested logit model estimated in section 2.3.1 (table 2.2) is obtained by defining the stochastic vector μ_{jmn} as constant over alternatives j belonging tot the same choice set m faced by respondent n (we will therefore drop the index j and use the notation μ_{mn}), and defining z_{jmn} as containing a dummy variable for each nest. This dummy has a value one for alternatives that are in the nest and a value 0 for alternatives that live outside the nest. In our specification we need two dummies δ_k: one δ_{ice} for ice alternatives and a second δ_{elc} for non-ice alternatives.

The stochastic vector μ_{mn} contains two independent terms μ_{kmn}, one for each dummy ($\mu_{ice,mn}$ and $\mu_{elc,mn}$ respectively). As mixing distribution for μ_{mn} we choose the normal distribution with an expected value of zero. The variance of both error terms is set to be identical. Hence both error terms are distributed identically and are independent for all choice sets m and respondents n.[13]

[13]For clarity we stress here the fact that we define a dummy for the non-ice nest although this is a single member nest and that we define both error terms to have an identical distribution. The reason for this will become clear in the remainder of this section.

The utility U_{jmn} can be rewritten as:

$$\begin{aligned} U_{jmn} &= \alpha' x_{jmn} + \sum_{k=1}^{K} \mu_{kmn}\delta_k + \epsilon_{jmn} \\ &= \alpha' x_{jmn} + \mu_{ice,mn}\delta_{ice} + \mu_{elc,mn}\delta_{elc} + \epsilon_{jmn} \end{aligned} \tag{2.9}$$

Any term of the utility U_{jmn} that is constant over the alternatives j in the same choice set m by respondent n drops from the choice probabilities.[14] We can hence define U'_{jmn} as:

$$\begin{aligned} U'_{jmn} &= U_{jmn} - \mu_{elc,mn} \\ &= U_{jmn} - (\delta_{ice} + \delta_{elc})\mu_{elc,mn} \\ &= \alpha' x_{jmn} + (\mu_{ice,mn} - \mu_{elc,mn})\delta_{ice} + \epsilon_{jmn} \end{aligned} \tag{2.10}$$

Both U'_{jmn} and U_{jmn} result in the same choice probabilities. From equation (2.10) we learn that in estimation it is not possible to identify the variance of both μ_{kmn} separately as only their sum enters the utility function (and hence the choice probabilities), already at this point it becomes clear why there is need to define both μ_{kmn} to have an identical distribution. The results are provided in table 2.3.[15] Note that the in the (calibrated) nested logit approximation the willingness to pay for different technological variables is identical to the original mixed logit estimation, as the ratio of the corresponding coefficients is constant.

So far there seems no problem in estimating a mixed logit model. The problem however arises when we want to use such a mixed logit specification for simulation in the framework of the TREMOVE model. Not only is the mixed logit setting computationally demanding, also considerable coding effort would be needed to include it in the TREMOVE framework. For this reason we now study how we can calibrate a nested logit specification that approximates the estimated mixed logit model in simulation.

Starting from the expression for U_{jmn} (equation (2.9)), we define U''_{jmn} by rescaling U_{jmn} with a factor a. We remind the reader that rescaling the utility does not affect the choice probabilities (see section 2.2), considered that utility maximisation applies (and rescaling does not change the relative order of the

[14]We recall that choice probabilities are not affected by a linear transformation $U'_{jmn} = aU_{jmn} + b$ of the stochastic utility U_{jmn} with a and b constant over the alternatives j belonging to choice set m faced by respondent n—note that a and b are not required to be constant over m and n.

[15]As both μ_{kmn} are independent normally distributed with identical variance, their difference (or sum as the normal distribution is symmetric) will again be distributed normal with a variance twice the value of $\mathrm{Var}(\mu_{kmn})$. Using one random term rather than two results in the same model but will significantly speed up model estimation. The estimated variance of the random term in the estimation output has then to be divided by two to match the model specification provided by equation 2.9.

Table 2.3. Calibrating a nested logit model using a mixed logit estimation

		ML estimation		NL approximation
Variable	Unit	coefficient α	p-value	coefficient β
Lifetime cost	€/km	−8,6254	0	−5,4921
Luggage space	0–1	1,2006	0	0,7644
Emissions	0–1	−0,9096	0	−0,5792
Range	100 km	0,3359	0	0,2139
Diesel		0,4668	0	0,2973
LPG		−0,7073	0	−0,4504
Alternative fuel		−0,2068	0,224	
Fuel cell		−0,8599	0,065	
Battery		−1,2702	0,016	−0,8088
Hybrid		−0,0192	0,803	
Var(μ_{kmn})		2,4123	0,049	
corresp. λ_{ice}				0,6367
Log likelihood		−1763,7819		

utilities of the alternatives).

$$U''_{nj} = aU_{nj} \tag{2.11}$$

with

$$a = \sqrt{\frac{\pi^2/6}{\pi^2/6 + \mathrm{Var}(\mu_{kmn})}} \tag{2.12}$$

We now define a nested logit approximation of the mixed logit specification (U''_{jmn}) by writing U^{NL}_{jmn} as:

$$U^{NL}_{jmn} = \beta' x_{jmn} + \epsilon^{NL}_{jmn} + \eta_{kmn} \tag{2.13}$$

with

- coefficient vector $\beta = a\alpha$
- error term ϵ^{NL}_{jmn} distributed independent and identically Gumbel for all alternatives j, choice situations m and respondents n with scale parameter $\sigma = a$
- error term η_{kmn} distributed so that $\max_{j \in S_k}(U^{NL}_{jmn})$ is independent and identically Gumbel distributed (with scale parameter normalised: $\sigma = 1$) for all nests k, choice situations m and respondents n.

Table 2.3 provides the coefficient values for the nested logit model defined by expression (2.13) for U^{NL}_{jmn} (we will come back at the calculation of the inclusive value coefficients λ_k later on). We will now study the difference between U^{NL}_{jmn} and U''_{jmn}.

The first two terms of U^{NL}_{jmn} are identical to the corresponding terms in U''_{jmn}. Considering that the remaining terms is constant over the alternatives j belonging to the same nest k in choice situation m by respondent n, this term does not affect the conditional choice probabilities[16] and hence the conditional choice probabilities are identical in both the mixed logit and nested logit specification.

We now define ϵ'_{kmn} as

$$\epsilon'_{kmn} = \max_{j \in S_k}(\beta' x_{jmn} + \epsilon^{NL}_{jmn}) \tag{2.14}$$

and from Ben-Akiva and Lerman (1985) we know that ϵ'_{kmn} is independent and identical Gumbel distributed for all nests k, choice situations m and respondents n with scale parameter $\sigma = a$ and expected value $E(\epsilon'_{kmn}) = aI_{kmn}$.[17]

Now we can rewrite $\max_{j \in S_k}(U^{NL}_{jmn})$:

$$\max_{j \in S_k}(U^{NL}_{jmn}) = \underbrace{\epsilon'_{kmn} + \eta_{kmn}}_{\text{Gumbel}} \tag{2.15}$$

Equation (2.15) defines the *error term* that controls the marginal choice between nests. For the nested logit specification we defined η_{kmn} so that this error term is Gumbel distributed with scale $\sigma = 1$ and hence the marginal choice is multinomial logit. Considering that the inclusive value coefficients λ_k are defined by equation (2.3) as the scale factor of the error terms at the level of the conditional choice (with the scale factor at the level of the marginal choice normalised to unity), it is easy to see that $\lambda_k = a$.

The error term corresponding to the marginal choice in the mixed logit model specified by expression (2.11) is defined by:

$$\max_{j \in S_k}(U''_{jmn}) = \underbrace{\max_{j \in S_k}(a\alpha' x_{jmn} + a\epsilon_{jmn})}_{\text{Gumbel}} + \underbrace{a\mu_{kmn}}_{\text{normal}} \tag{2.16}$$

The first term is Gumbel distributed with scale parameter $\sigma = a$ (Ben-Akiva and Lerman, 1985), whereas the second part is normal by definition.

In figure 2.3 and 2.4 we compare the stochastic distribution of the marginal choice error terms of the mixed logit estimation (expression (2.16)) and the corresponding nested logit approximation (expression (2.13)) presented in table 2.3 ($\lambda = 0{,}6367$).[18] The difference between both curves is a measure for the difference in choice behaviour at the marginal choice level. It is easy to see that the difference becomes smaller as λ approaches one.

[16]The conditional choice is the choice between alternatives in the same nest (see appendix A).

[17]I_{kmn} is the inclusive value of nest k in choice situation m by respondent n (see section 2.2).

[18]The functions have been shifted horizontally such that the expected value is zero, remember that adding any constant factor does not change the choice probabilities so any horizontal shift in order to better illustrate the fit of both curves does not affect the model qualitatively.

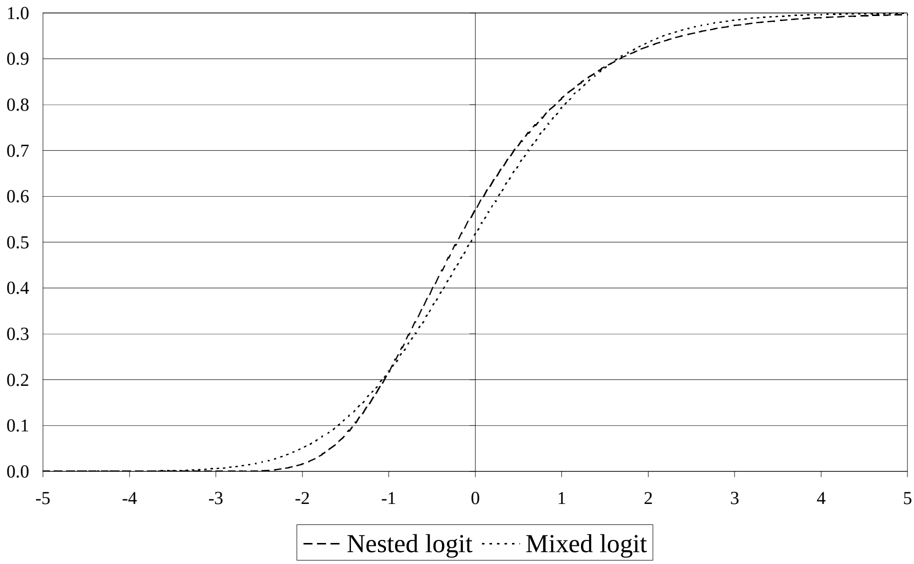


Figure 2.3. Cumulative distribution function $F(x)$ of stochastic utility at the marginal choice level for model coefficient values presented in table 2.3

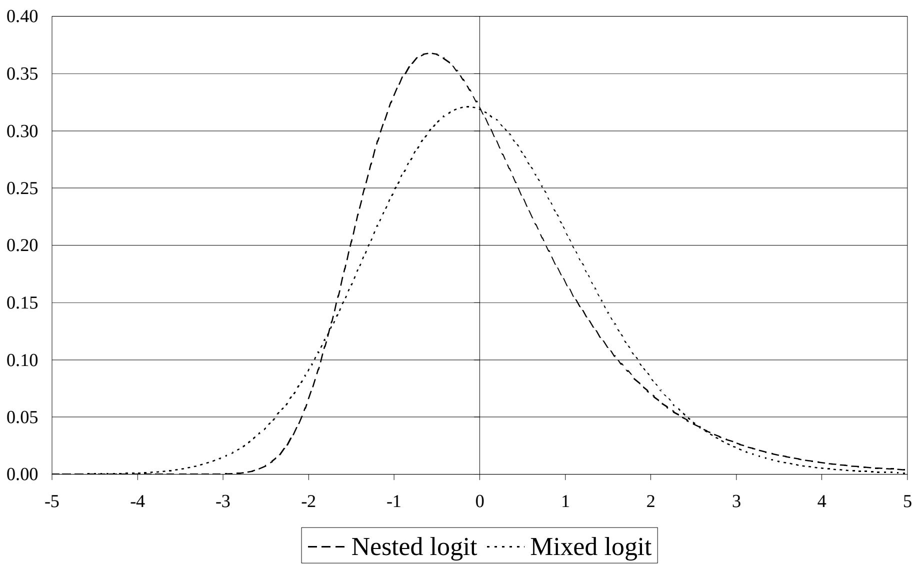


Figure 2.4. Probability density function $f(x)$ of stochastic utility at the marginal choice level for model coefficient values presented in table 2.3

An interesting exercise is to compare the nested logit model in table 2.3 to the one in table 2.1. Differences in coefficient values are small, especially compared to the coefficient confidence interval (table 2.1), providing an indication that the impact of the differences in the probability distribution of the error term controlling the marginal choice is probably small.[19]

As a last remark (and for completeness) we elaborate a little on our choice for the factor a (equation (2.12)). In fact, there is no evidence that our choice for a results in the best nested logit approximation to the mixed logit specification. It is interesting to note that a change in the definition of a mainly results in a change of the variance of η_{kmn} as the scale parameter σ (and hence the variance) of the Gumbel error term at the marginal choice level is fixed to one. It can be shown that using our definition of a results in the covariance for alternatives in the same nest to be identical in both the mixed logit and corresponding nested logit specification (Batley et al., 2003).

2.3.3. Repeated choice

The reader may now wonder whether we did not miss the point in the last section. Apparently our methodology allows to formulate a nested logit model that approximates a computationally demanding mixed logit estimation, whereas it is much easier to directly estimate the nested logit model specification without having the drawback of being an approximation to reality. This is a correct observation—as far as the example in the previous section is concerned.

As it has been noted earlier, the nested logit model does not allow to account for repeated choice situations: the η_{kmn} in equation (2.13) are independent for all choice situations m and all respondents n. As it has been discussed in chapter 1, mixed logit model specifications that account for repeated choice result in a significantly better estimation result using the survey data set. Table 2.4 compares both modelling frameworks.

The mixed logit model has the drawback that it is computationally demanding, but this is a real problem in simulation only. The disadvantage of nested logit is the inability to account for repeated choice situation, but such a specification is limited to estimation only.[20] The methodology discussed in the previous section allows to use mixed logit for estimation and in a next step calibrate a nested logit model to be used in simulation—this is the real interest

[19]For completeness we note that we now have three similar models: a nested logit estimated model, a mixed logit estimated model and a nested logit model specified as an approximation to the estimated mixed logit model. All three specifications are different and finding both nested logit models to be similar actually does not tell much about how similar any of them is to the mixed one. The use of the comparison is however in the finding that the nested logit model coefficients derived from the mixed logit estimation do not differ much from what we get when we estimate the coefficients of the same nested logit specification directly on the dataset.

[20]In simulation we face a single choice situation.

Table 2.4. Mixed logit versus nested logit

Characteristic	Nested	Mixed
Can account for repeated choice	No	Yes
Closed expression for choice probabilities	Yes	No
Can account for correlation in preferences	Yes	Yes

of the methodology developed in section 2.3.2. This way we both account for repeated choice and still have an efficient simulation model specification.

We will now apply the methodology by re-estimating the model in table 2.3 but defining the error terms μ_{kn} (see equation (2.9)) to be constant over choice situations m faced by the same respondent n (as opposed to μ_{kmn} which is independent over m). This results in the mixed logit estimation in table 2.5. We have added the calibrated nested logit approximation to the same table. In the simulation model we do not include insignificant coefficients.[21]

So we now got up to the point where we have calibrated a nested logit simulation model that accounts for the repeated choice character of the estimation data set. We can however go one step further and estimate the two-level structure in figure 2.5. This model is represented in table 2.6. At two levels we define error terms $\mu_{1,kn}$ and $\mu_{2,kn}$ for all nests k, with a variance $\mathrm{Var}(\mu_{1,kn})$ at the lower level and $\mathrm{Var}(\mu_{2,kn})$ at the upper level and distributed independent

[21] Remember that in the stated preference data set the choice variables x_{jmn} are uncorrelated (orthogonal design of choice sets).

Table 2.5. Calibrated nested logit model using a mixed logit estimation (accounting for repeated choice in the estimation data set)

		ML estimation		NL approximation
Variable	Unit	coefficient α	p-value	coefficient β
Lifetime cost	€/km	−9,5847	0	−5,4590
Luggage space	0–1	1,3158	0	0,7494
Emissions	0–1	−0,9357	0	−0,5329
Range	100 km	0,3454	0	0,1967
Diesel		0,4683	0	0,2667
LPG		−0,6851	0	−0,3902
Alternative fuel		−0,1765	0,284	
Fuel cell		−1,0304	0,005	−0,5869
Battery		−1,5074	0	−0,8585
Hybrid		−0,0264	0,731	
$\mathrm{Var}(\mu_{kn})$		3,4260	0	
λ_{ice}				0,5695
Log likelihood		−1629,4757		

for both levels, all nests k and all respondents n. The corresponding inclusive value coefficients are λ_{fuel} and λ_{ice}.[22]

To limit the computational demands of the estimation process we limited the accuracy to a lower level compared to the previous estimations with one or two error terms. Although this considerable speeds up the estimation procedure, estimating the model with the gllamm procedure in Stata was still time consuming (in the order of days).[23]

The second level cannot be estimated in a nested logit specification, as single choice sets do not provide information on correlation in preferences for e.g. diesel cars (each choice set contains only one diesel car). This can be easily verified from equation (2.4) where the log-sum coefficients for single-member nests drop in the expression for the choice probabilities. However, by accounting for repeated choices this correlation can be measured across different choice sets faced by the same respondent in a mixed logit specification.

The reader may now get the impression that we got somehow lost in calibrating coefficients that drop from the choice probability expressions in a nested logit simulation setting. This is again a correct observation at this point, but in the next section we will show the interest of the estimated two-level

[22]We could also define a λ_{elc1}, but this coefficient drops from the choice probabilities and is of no interest for the further discussion. In the specification of this model some error terms add up such that the estimation procedure could be limited to five independent error terms, four of them having an identical variance (see also section 2.3.2).

[23]To get an indication of the possible impact of accuracy level, we estimated a simple model with one error term μ_n at different levels of estimation accuracy. The results indicated that a higher accuracy results in a lower LL (absolute value) and typically higher estimated variance for μ_n. So it may be that we here understate the variance of μ_n and hence obtain a value for λ which is closer to unity.

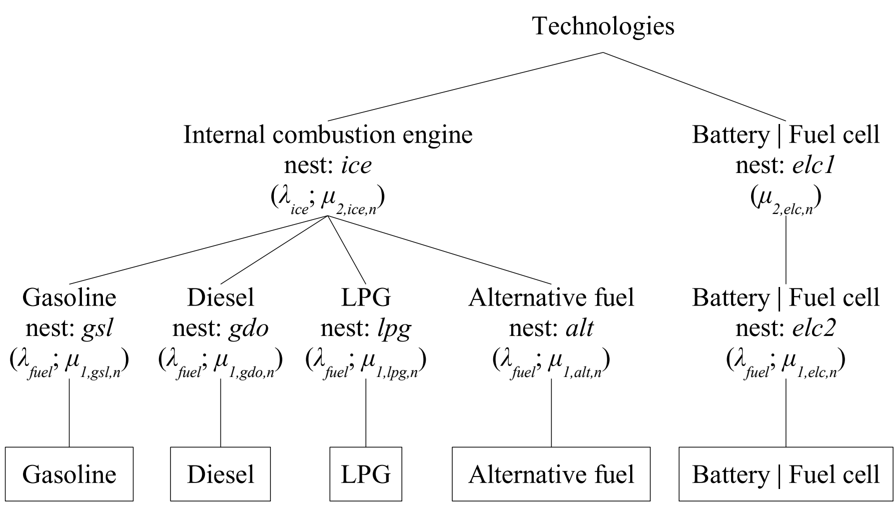


Figure 2.5. Extended nested structure

Table 2.6. Extended nested structure estimated as mixed logit

Variable	Unit	MXL estimation coefficient	p-value	NL calibration coefficient
Lifetime cost	€/km	−14,0789	0	−7,2608
Luggage space	0–1	1,5721	0	0,8108
Emissions	0–1	−1,1880	0	−0,6127
Range	100km	0,4147	0	0,2139
Diesel		0,7759	0	0,4002
LPG		−0,9448	0,001	−0,4873
Alternative fuel		−0,2065	0,458	
Fuel cell		−0,3492	0,409	
Battery		−0,8453	0,050	−0,4360
Hybrid		−0,0217	0,824	
$\text{Var}(\mu_{2,kn})$		1,5420	0,017	
λ_{ice}				0,8664
$\text{Var}(\mu_{1,kn})$		2,9977	0	
λ_{fuel}				0,5952
Log likelihood		−1428,9027		

structure when we discuss the technological scope of the simulation tool.

2.3.4. Technological scope

At the point where we are now, we pushed the estimation of the mixed logit and the corresponding approximation by nested logit to the limits of the information contained by our data set—even up to the point that we calibrated coefficients that drop from the choice probabilities in our nested logit simulation model. There is however still one main limitation of the simulation tool designed: it accommodates for five alternative technologies only, whereas it seems useful if we could add some more in simulation, such as two technologies running on alternative fuels (e.g. hydrogen and CNG), or a hybrid and a conventional version of the diesel car. In this section we propose an extension of the model to overcome this barrier.

We will first examine the situation of a conventional and hybrid diesel. Based on equation (2.13) we can express the utility U_{jn}^{NL} of both alternatives as:[24]

$$U_{jn}^{NL} = \beta' x_{jn} + \epsilon_{jn}^{NL} + \eta_{2,ice,n} + \eta_{1,gdo,n} \tag{2.17}$$

The conditional choice between both alternatives (conventional and hybrid) is the conditional choice in the diesel nest of the nested logit model represented in figure 2.5. We can hence accommodate for both alternatives in the nested

[24]The single choice simulation setup allows us to drop the index m from here on in order to avoid clutter in the expressions.

logit choice model by including both in the fuel nest at the lowest level of the structure (see figure 2.5).

Extending the model to account for a battery and fuel cell car in the same choice set can be done in a similar way.

If we want to include two alternatives running on an alternative fuel (e.g. ethanol and CNG), the methodology becomes somewhat less straightforward. One could argue that they should simply enter the nest of alternative fuel technologies, but it may be more appropriate to define a separate error term $\eta_{2,alt2,n}$ reflecting the observation that the nesting structure is fuel based, and it concerns two different (alternative) fuels, a separate nest should be defined for each fuel. We will opt for the last choice here, as it better matches our intuition.

Applying the methodology presented in this section, we constructed a nested logit simulation tool that accommodates the full technological scope defined in table 2.7 (based on Verbeiren et al., 2003). Figure 2.6 provides an overview of its nested structure. The coefficients β and the inclusive value coefficients λ_i are those presented in table 2.6.

2.4. Integration in TREMOVE

In the previous section we discussed how to design a flexible simulation tool based on stated preference data. In this section we compare the result to a revealed preference based technology choice model. In a second step we study the integration of both simulation models in order to combine the strong points of the stated and the revealed preference approach.

Table 2.7. Technological scope of the simulation tool

Technology
Gasoline
Gasoline hybrid
Diesel
Diesel hybrid
LPG
CNG
CNG hybrid
Hydrogen
Hydrogen hybrid
Hydrogen fuel cell
Battery electric

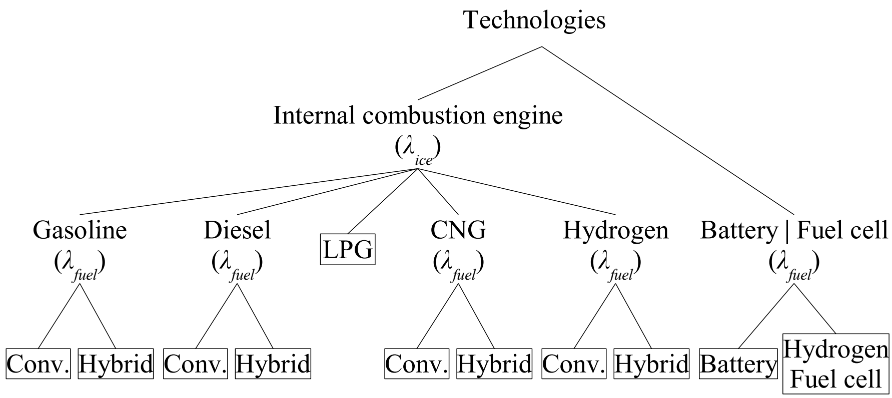


Figure 2.6. Nested logit simulation model covering the full technological scope

2.4.1. The TREMOVE 2 RP model

In this section we provide an overview of a *revealed preference* (RP) private car technology choice model that was designed for the TREMOVE 2 partial equilibrium model (G. De Ceuster et al., 2005). The discussion will focus here on the RP estimated part of the private car technology choice model, this is without the extension for hybrids.[25]

In the TREMOVE 2 model the car market is segmented based on fuel (diesel and gasoline) and engine size (small $< 1{,}4\,$l; medium 1,4–2,0 l and big $> 2{,}0\,$l), resulting in six segments. The technical specifications of the larger TREMOVE framework results in two separate technology choice models, one for the segments (diesel and gasoline) with an engine size under 1,4 l, and another for engine sizes over 1,4 l (4 segments). The discussion in this and next section will focus on the model for the larger engine sizes, the extension to the small size class is straightforward.

The segmentation over *engine size* class is rather uncommon in technology choice modelling and stems from the emissions model applied in TREMOVE 2. The COPERT III methodology (Ntziachristos and Samaras, 2000) specifies emission factors which are function of the engine size class. The scope of the technology choice model has hence been defined to cover preferences for different engine sizes. There seems to be correlation between the engine size class and the marketing based body type classification as used e.g. by Verboven (1996), COWI A/S (2002) and Verboven (2002b). We should however be careful in comparing different models, as different car variables tend to correlate in RP data sets.[26]

[25] The extension to include hybrids in TREMOVE 2 was not implemented making use of RP data, considered the very limited supply of hybrid technologies in the period covered by the RP data set.

[26] E.g. Brownstone et al. (2000) mention this correlation as a major difficulty in estimating RP

The *estimation procedure* followed for the TREMOVE 2 technology choice model is somewhat different from what is typically found in literature. Verboven (1996), De Jong (1996), COWI A/S (2002) and Verboven (2002b) all use extended data sets of sales of individual car models, whereas for the estimation of the TREMOVE 2 technology choice model aggregate, market share data were used. The combined cross-section and time series data set covers national quarterly sales data over a period of about two years (1999–2000) for 17 European countries. The model specification is nested logit (nested structure see figure 2.7) and the coefficients β and λ are presented in table 2.8.

The TREMOVE 2 technology choice model includes two generic variables: the lifetime cost and the acceleration. The *lifetime cost* variable has been discussed in section 2.3.1 and is a composite user cost variable reflecting all purchase, annual and per kilometre costs. The *acceleration* is a variable that acts as a proxy for performance. The *GDP per inhabitant* variable enters the model as a proxy for (average) income.

Experience with the TREMOVE 2 model has caused some discussion regarding the impact of changes in user prices on the diesel-gasoline market shares. Some experts feel that price sensitivity of the car technology choice model may be underestimated. We decided to stick in our application to the existing approach and leave the issue to be addressed by further research on the topic.[27]

2.4.2. Integration of SP and RP model

In the previous section (2.4.1) we introduced a revealed preference estimated nested logit choice model, whereas in section 2.3 we designed a nested logit simulation model based on stated preference. In this paragraph we will

car choice models.

[27]Using a more extended data set (covering an extended time span) or a more detailed technology classification scheme that closer follows consumer preferences rather than emissions characteristics may enhance consensus on the technology choice model specification, alternatively one may think of a model that is calibrated using evidence from existing research.

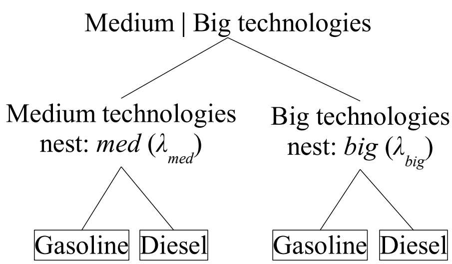


Figure 2.7. Nested structure of the TREMOVE 2 choice model for medium (1,4–2,0 l) and big (> 2,0 l) technologies

Table 2.8. TREMOVE 2 revealed preferences estimated car technology choice model for Belgium

Variable	Unit	coefficient β
LFC/quarterly GDP per inh.	LFC in €2000/km; GDP in 10k €95	−0,4585
Acceleration	s from 0 to 100 km/h	−0,04557
Diesel (Belgium)	dummy	0,1939
Big	dummy	−2,5105
Quarterly GDP × big	interaction in 1000 €95	0,1738
λ_{med}		0,1101
λ_{big}		0,1563

discuss the *integration* of both models into one tool that allows to cover the full technological scope for private cars (see table 2.7) and take advantage of the strong points of both the SP and RP approach.

How do both models differ?

If we compare the stated preference (SP) model (table 2.6) and the revealed preference (RP) model (table 2.8), we see that both models have the lifetime cost variable in common. In the RP model this variable however enters in a relative way, divided by the GDP. To allow for a comparison of both models, we rescale the lifetime cost variable in the SP model by dividing it by the Belgian GDP per capita at the time of the survey. We provide an overview of both the SP and the RP model (for Belgium) using the relative lifetime cost variable in table 2.9.

When comparing both models, we should take into account two issues. A first issue is related to the definition of the nested logit model, which normalises the variance of the stochastic utility of the marginal choice at the *top level* (see section 2.2). The top level choice is not the same in both models: in the RP model this is the choice between the medium and big technology nests, whereas in the SP model the top level choice considers ice technologies versus battery electric or fuel cell cars.

A second issue is that through the normalisation at the top level, a *scaling factor* (representing the variance in stochastic utility) is confounded with the coefficient values (see equation (2.4)). This scaling factor may be different between data sets.

The first issue can be addressed by considering the conditional choice at a level that is common to both models. Both the RP and the SP model feature the choice between diesel and gasoline technologies. To avoid notational clutter in the expressions, we will simplify the nesting structure of the SP model (see figure 2.6) somewhat and exclude the diesel and gasoline hybrid technologies, such that the diesel and gasoline nests in the SP simulation model collapse

Table 2.9. SP and RP nested logit model coefficients

Variable	Unit	SP coefficient	RP coefficient
LFC/quarterly GDP	LFC in €/km GDP in 10k €	−4,4164	−0,4585
Luggage space	0–1	0,8108	
Emissions	0–1	−0,6127	
Range	100 km	0,2139	
Acceleration	s		−0,04557
Diesel		0,4002	0,1939
LPG		−0,4873	
Battery		−0,4360	
Big			−2,5105
quarterly GDP × big	10k €		1,738
λ_{ice}		0,8664	
λ_{fuel}		0,5952	
λ_{med}			0,1101
λ_{lar}			0,1563

(single member nests). For the SP model, this conditional choice probability for the diesel (gdo) technology is then:[28]

$$P^{SP}_{gdo|S_{ice}} = \frac{e^{(\hat{\beta}^{SP})' x_{gdo} / \lambda^{SP}_{ice}}}{e^{I_{ice}}} \tag{2.18}$$

For the RP model, the conditional choice probability for diesel in the medium nest is:

$$P^{RP}_{gdo|S_{med}} = \frac{e^{(\hat{\beta}^{RP})' x_{gdo} / \lambda^{RP}_{med}}}{e^{I_{med}}} \tag{2.19}$$

To compare the variances in unobserved utility between both marginal choice models, we cannot apply formula (2.2) straightforwardly. We should remind here that the estimated coefficients $\hat{\beta}$ in the nested logit equals to the original β divided by the σ associated to the upper model (marginal choice between nests):

$$\hat{\beta}^{SP} = \beta^{SP} / \sigma^{SP} \tag{2.20}$$

With $\lambda^{SP}_{ice} = \sigma^{SP}_{ice} / \sigma^{SP}$ (see section 2.2), this becomes:

$$\sigma^{SP}_{ice} = \frac{\beta^{SP}}{\hat{\beta}^{SP}} \lambda^{SP}_{ice} \tag{2.21}$$

Similarly, for the conditional choice in the medium nest of the RP model:

$$\sigma^{RP}_{med} = \frac{\beta^{RP}}{\hat{\beta}^{RP}} \lambda^{RP}_{med} \tag{2.22}$$

[28] From here on, we drop the index n considering the TREMOVE 2 model does not distinct different consumer categories. The variables however do evolve over time, this time-dependency is not specifically included in any notation here.

The ratio r of variance in unobserved utility associated to the conditional choice diesel-gasoline is then:

$$r = \left(\frac{\sigma_{ice}^{SP}}{\sigma_{med}^{RP}} \right)^2 = \left(\frac{\lambda_{ice}^{SP}}{\hat{\beta}^{SP}} \frac{\hat{\beta}^{RP}}{\lambda_{med}^{RP}} \right)^2 \tag{2.23}$$

Using the relative lifetime cost coefficient of the two models, we get:[29]

$$r = \left(\frac{0{,}8664}{-4{,}4164} \frac{-0{,}4585}{0{,}1101} \right)^2 = (0{,}8174)^2 = 0{,}6674 \tag{2.24}$$

This means that the variance in unobserved utility for the marginal choice between diesel and gasoline is lower in the stated preference than in the revealed preference data set by a factor of approximately 1,5.

There seems no obvious reason for this ratio k to be smaller or larger than one. In a joint RP/SP model estimation exercise by Brownstone et al. (2000) scaling factors (this is the square root of the r reported above) both smaller and larger than one were reported depending on the model specification. The scale ratios are in the same order of magnitude of what we obtain.

The higher variance observed in the RP choice model can be explained by the different choice situation studied compared to the SP model. In the survey used for the SP model, alternatives were mentioned to differ only in the attributes indicated (and captured in model estimation). In the RP data set technologies were defined by average engine size, fuel, lifetime cost and acceleration of the cars sold in the corresponding segment, but probably also differ in other characteristics which were not included in the model.

Referring back to the remark on the sensitivity of the TREMOVE 2 RP model (see section 2.4.1) we add to the discussion our finding of a rather moderate scale difference between the RP and the SP model to the discussion.

Integration of the RP and SP models

In the previous paragraph we showed how the RP and the SP models differ in variance of unobserved utility. Furthermore, we indicated differences in the nested logit structure between both models. To integrate both models, we will propose a methodology that results in a unified nested model.

The joint estimation of SP/RP models is discussed in Ben-Akiva and Morikawa (1997); Brownstone et al. (2000). The methodology applied comes down to including in the estimation process an additional parameter which scales the SP estimation data. Brownstone et al. (2000) applies this methodology to the multinomial logit model and the mixed logit model, whereas

[29] We report in this chapter rounded figures with four decimals, therefore any calculated results may marginally deviate from the result obtained by using the rounded figures as input.

Ben-Akiva and Morikawa (1997) defines the problem as a nested logit model in order to use the log-sum coefficient as the scaling parameter.

The setting we are using is however somewhat different from past research. First of all, we observe that both data sets have only one generic variable in common (the lifetime cost).[30] We will see that with only one common variable, estimation for both data sets can be done separately and scaling of one data set can be done afterwards—the resulting model will be identical to what we would obtain if the log likelihood was optimised in a joint estimation including the data set scaling parameter.

A second difference is that in most past studies, the SP and RP data set considered choices made by the same respondents. This is not the case in our study. The data sets used for both models differ in many characteristics: the SP data set is based on individual choices made by a sample of the Flemish households, whereas the RP data set included aggregate (quarterly) data of all car sales in EU countries over a two year period. This means that the difference in scale between both models (SP and RP) reflects these differences in data set specifications (and not only the difference between revealed and stated behaviour).

Finally, we want to integrate two nested logit models with different nesting structures, which is an extension to most past studies where both separate models had been specified as MNL or MNL and MXL.

The stochastic utility of alternative j in the revealed preference and stated preference models when estimated separately can be expressed as (see section 2.2):

$$\begin{cases} U_j^{RP} = \beta_x^{RP} x_j + \beta_{LFC}^{RP} LFC_j + \epsilon_j^{RP} + \eta_{size}^{RP} \\ U_j^{SP} = \beta_y^{SP} y_j + \beta_{LFC}^{SP} LFC_j + \epsilon_j^{SP} + \eta_{fuel}^{SP} + \mu_{ice}^{SP} \end{cases} \tag{2.25}$$

with:

- LFC_j the lifetime cost (see equation (2.7)), x_j the vector of variables that only enter the RP model and y_j the vector of variables that only enter the SP model
- ϵ_j^{RP} independently Gumbel distributed over all alternatives j and choice situations with scale parameter $\sigma = \lambda_{size}^{RP}$
- η_{size}^{RP} independent over all choice situations and size nests such that $\max_{j \in size}(U_j^{RP})$ is Gumbel distributed with scale parameter $\sigma = 1$ (normalised)
- ϵ^{SP} independently Gumbel distributed over all alternatives and choice situations with scale parameter $\sigma = \lambda_{fuel}^{SP} \lambda_{ice}^{SP}$

[30]Both models also have the *dummy* variable for diesel technologies in common. The role of the dummies in model estimation is to capture all choice preferences that could not be explained by the generic and/or interaction variables. As the RP dummy is estimated based on observed market shares, we will use this dummy in simulation rather than the SP estimated one.

- η^{RP}_{fuel} independent over all choice situations and fuel nests and ice nests[31] such that $\max_{j\in ice}(U^{SP}_j)$ is Gumbel distributed with scale parameter $\sigma = \lambda^{SP}_{ice}$
- η^{RP}_{ice} independent over all choice situations and ice nests such that $\max_{j\in fuel}(U^{SP}_j)$ is Gumbel distributed with scale parameter $\sigma = 1$ (normalised)

For the integrated model (IG) we will first propose an expression for the stochastic utility U^{IG}_j that allows for the correlation-substitution patterns of the individual RP and SP models. In a next step we calibrate the values for the IG model coefficients using the separate RP and SP estimations. The stochastic utility U^{IG}_j of alternative j is:

$$U^{IG}_j = \beta^{IG}_x x_j + \beta^{IG}_y y_j + \beta^{IG}_{LFC} LFC_j + \epsilon^{IG}_j + \eta^{IG}_{fuel} + \eta^{IG}_{ice} + \eta^{IG}_{size} \tag{2.26}$$

with

- ϵ^{IG}_j independently Gumbel distributed over all alternatives j and choice situations with scale parameter $\sigma = \lambda^{IG}_{fuel}\lambda^{IG}_{ice}\lambda^{IG}_{size}$
- η^{IG}_{fuel} independent over all choice situations, fuel nests, ice nests and size nests such that $\max_{j\in fuel}(U^{IG}_j)$ is Gumbel distributed with scale parameter $\sigma = \lambda^{IG}_{ice}\lambda^{IG}_{size}$
- η^{IG}_{ice} independent over all choice situations, ice nests and size nests such that $\max_{j\in ice}(U^{IG}_j)$ is Gumbel distributed with scale parameter $\sigma = \lambda^{IG}_{size}$
- η^{IG}_{size} independent over all choice situations and size nests such that $\max_{j\in size}(U^{IG}_j)$ is Gumbel distributed with scale parameter $\sigma = 1$ (normalised)

The corresponding nesting structure is presented in figure 2.8.

We will now show how to identify the values for β^{IG}_x, β^{IG}_y, β^{IG}_p based on the RP and SP estimated models specified by equation (2.25).

To replicate the choice behaviour of the RP model, it is easy to see that following conditions have to apply to the coefficients of the IG model:

$$\begin{cases} \beta^{IG}_x = \beta^{RP}_x \\ \beta^{IG}_{LFC} = \beta^{RP}_{LFC} \\ \lambda^{IG}_{ice}\lambda^{IG}_{size} = \lambda^{RP}_{size} \end{cases} \tag{2.27}$$

In our calibration of the integrated model U^{IG} on the information contained by the SP estimated model, we follow the approach discussed in

[31] With *ice nests* we indicate two nests, one including the alternatives with an ice engine and a second nest regrouping the non-ice alternatives.

literature and add a scaling parameter s to the choice variables in expression (2.26):

$$U^{IG}_{SP} = \beta^{IG}_{y} sy + \beta^{IG}_{LFC} sLFC + \epsilon^{IG} + \eta^{IG}_{fuel} + \eta^{IG}_{ice} + \eta^{IG}_{size} \tag{2.28}$$

The role of the scaling parameter s in the calibration procedure is in fact setting the scale of the stochastic utility of U^{IG} equal to the (stochastic) behaviour captured by the RP model which is expected to reflect real world behaviour (Brownstone et al., 2000).[32]

Before we can compare this expression to the SP estimated model, we need to transform it. In the stated preference model the choice alternatives all have the same size, so the error term η^{IG}_{size} is a constant within each choice set rather than a stochastic variable. Recalling that any linear transformation of the stochastic utility does not affect the choice outcome under utility maximisation (as long as transformation parameters are constant over each choice set), we drop η^{IG}_{size} and rescale the utility U^{IG} with a factor λ^{IG}_{size} in order to re-normalise the scale parameter of the stochastic utility[33] to unity:

$$U^{IG}_{SP} = \frac{1}{\lambda^{IG}_{size}} \left(\beta^{IG}_{y} sy + \beta^{IG}_{LFC} sLFC + \epsilon^{IG} + \eta^{IG}_{fuel} + \eta^{IG}_{ice} \right) \tag{2.29}$$

From the expressions for U^{IG}_{SP} and U^{SP} follows the calibration of the integrated model:

$$\begin{cases} \beta^{IG}_{LFC} s / \lambda^{IG}_{size} = \beta^{SP} LFC \Rightarrow s = \lambda^{IG}_{size} \beta^{SP}_{LFC} / \beta^{RP}_{LFC} \\ \beta^{IG}_{y} = \beta^{SP}_{y} \lambda^{IG}_{size} / s = \beta^{SP}_{y} \beta^{RP}_{LFC} / \beta^{SP}_{LFC} \\ \lambda^{IG}_{ice} \lambda^{IG}_{size} / \lambda^{IG}_{size} = \lambda^{SP}_{ice} \Rightarrow \lambda^{IG}_{size} = \lambda^{SP}_{ice} \\ \lambda^{IG}_{fuel} \lambda^{IG}_{ice} \lambda^{IG}_{size} / \lambda^{IG}_{size} = \lambda^{SP}_{fuel} \lambda^{SP}_{ice} \Rightarrow \lambda^{IG}_{fuel} = \lambda^{SP}_{fuel} \end{cases} \tag{2.30}$$

As discussed above, we see that there is no need for a joint estimation to determine s when only one (generic) variable is common to both data sets.

Provided that all resulting log sum coefficients λ_k are between zero and one, the model is consistent with random utility maximisation.

The final model combines the strong points of RP and SP estimation:

- SP allows for a clear identification of trade-off between variables, as the choice sets were constructed to avoid correlation.
- SP allows to collect information on choice behaviour regarding alternative technologies as well as alternative (ranges of) variables.
- RP provides information on the real world variance in the stochastic utility.

[32] Note that under utility maximisation scaling the deterministic part of utility is equivalent to scaling the stochastic part.

[33] The stochastic part of the utility U^{IG}_{SP} is $\epsilon^{IG} + \eta^{IG}_{fuel} + \eta^{IG}_{ice}$ which is by definition distributed Gumbel with a scale parameter $\sigma = \lambda^{IG}_{size}$.

- RP provides information on some variables that had been excluded in the survey, such as performance (through acceleration) and vehicle engine size.

The final integrated model is presented figure 2.8 and its coefficients β and λ in table 2.10.

2.5. Conclusions

In the chapter we studied the design and estimation of an efficient simulation model based on stated preference. We provided a methodology that allowed to stick to the nested logit in simulation while applying the mixed logit specification in estimation in order to account for the repeated choice character of the survey based data set.

The stated preference model was further integrated with the existing revealed preference model from the TREMOVE 2 framework. We discussed an approach that allows to combine the advantages of both modelling approaches and indicated how the nested structures can be merged in order to create an integrated model.

The chapter finally provides an extended simulation tool that covers the technological scope as presented in table 2.7.

In a subsequent chapter we will include the model presented here in the TREMOVE framework in order to make an environmental and welfare

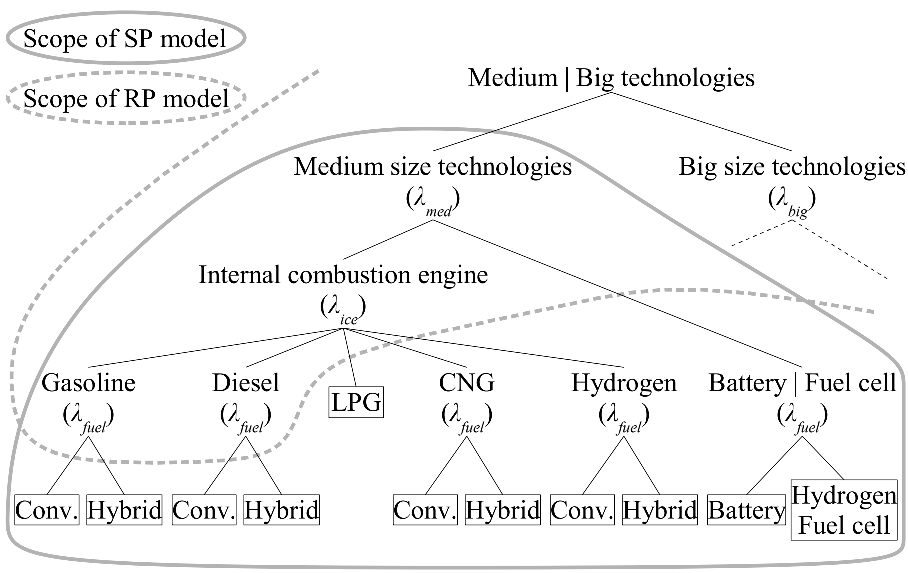


Figure 2.8. Final nested logit simulation model

Table 2.10. Coefficients of final nested logit simulation model

Variable	Unit	coefficient β^{IG}
LFC/quarterly GDP	LFC in €/km GDP in 10k €	−0,4585
Luggage space	0–1	0,08418
Emissions	0–1	−0,06361
Range	100 km	0,02220
Acceleration	s	−0,04557
Diesel		0,1939
LPG		−0,05059
Battery		−0,04526
Big		−2,5105
quarterly GDP × big	10k €	1,738
λ_{ice}		0,8664
λ_{fuel}		0,5952
λ_{med}		0,1270
λ_{lar}		0,1804

assessment of the different private car technologies.

CHAPTER 3

Do we want cleaner cars?

3.1. Introduction

Concerns about environmental pollution linked to transport activity raise the question on how we can reduce emissions from private cars. Considerable research efforts have been devoted to the development of cleaner fuels and car technologies, which seem to have some environmental potential. The aim of this chapter is to make an assessment of the environmental and welfare impact of a shift from conventional to alternative vehicle technologies.

In this chapter we conduct an analysis of the environmental performances of conventional gasoline and diesel technologies and compare them to a selection of new fuels and technologies for private cars: hybrid transmission, electrical battery cars, CNG cars, LPG cars, hydrogen fuel cell cars, etc (figure 3.2 defines the technical scope of this chapter).

We describe how we include the new technologies in the framework of the TREMOVE Belgium model. TREMOVE is a partial equilibrium representation of the transport markets (all modes for passenger and freight transport) that was originally developed for the European Commission during the Auto-Oil II program in 1998–1999 and updated to version 2 in 2005. We discuss how we can apply the TREMOVE modelling framework, integrate the technology choice model that has been developed in chapter 2, and define a baseline evolution for the alternative technologies reflected in figure 3.2.

The simulation of an emission tax guarantees that emissions are reduced at the lowest cost for society (Kolstad, 2000). By simulating such a scenario with TREMOVE we can study how this reduction is obtained and which technologies contribute to it. The size of the environmental benefits is compared to corresponding social costs to draw conclusions on the net welfare impact.

3.2. Modelling transport emissions

The focus of this chapter is to study the contribution of new technologies to a reduction of overall transport emissions, and the related welfare impact of this environmental improvement. To allow for such an assessment we need a modelling tool that represents all transport markets, includes a vehicle stock representation, has an emissions module and translates impacts to welfare costs. The TREMOVE Belgium modelling framework provides most of the features we need (see figure 3.1—extensions to the model discussed in this chapter are indicated in *italics*) and therefore we select it as a starting point for the simulations in this chapter.

A concise overview of the TREMOVE Belgium model specification as well as its calibration is provided in appendix C. We will discuss in this chapter the emissions module and the extensions (indicated in *italics* in figure 3.1) to the model necessary for our study.

3.2.1. The choice for alternative technologies

Private cars

In chapter 2 we discussed the design of a model for the simulation of the choice for conventional and alternative private car technologies. The model was designed to be compatible with the TREMOVE framework so its application here is straightforward. The structure of the TREMOVE framework requires two technology choice models, one for small engine size technologies and a second for medium and big engine sizes. We present the nested structure of the medium-big choice model in figure 3.2. The model for small

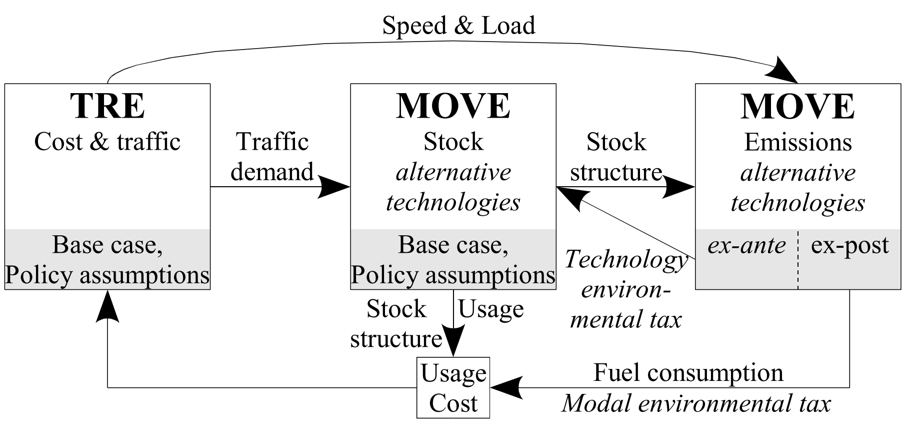


Figure 3.1. The TREMOVE Belgium modelling framework (*italics*: extensions discussed in this chapter)

technologies has the same structure (without the top-level size choice). The model coefficients are presented in table 3.1.

Some special attention has to be paid to the class of small diesel vehicles (engine size under 1,4 litre). This conventional car technology class had only very small market share in the past. More recently more car models became available on the market and their market share increased. Studying a random sample of car types that are sold in the small gasoline class, we observed that the corresponding diesel type often has an engine that is slightly larger than 1,4 litre and thus is classified as medium sized. Hence, we assume the potential of this small engine diesel class to be more limited compared to the medium and large classes. In the design of our discrete choice model the estimation of the dummy variable for the diesel technologies was based on observations for the medium and large class only. We hence feel the need for an adapted dummy for the small class. Lacking sufficient data, we fixed this dummy to an arbitrary value of −0,1, which corresponds to a simulated market share of about 8% of the small cars in 2005 (more details on the baseline simulation in section 3.4).[1]

The dummy for the LPG technologies was estimated in chapter 1 making use of a stated preference data set (survey) where the LPG cars were presented as dedicated new vehicles. Using this dummy (with value −0,05), the simulated market shares (in the order of magnitude of 10%) are significantly

[1] As indicated in chapter 1 the role of the dummies in the choice model is to represent all choice preferences for a technology that can not be explained by the generic variables. In the estimation procedure the value of the dummy coefficient is determined such that modelled technology shares are brought in line with the shares observed in the estimation dataset.

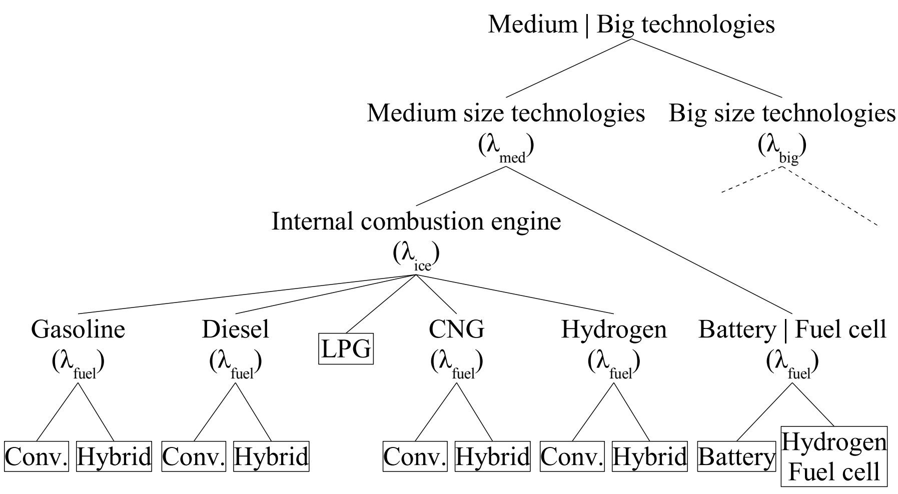


Figure 3.2. Structure of the nested logit choice model for medium and big private car technologies

Table 3.1. Coefficients of nested logit simulation model based on chapter 2

Variable	Unit	Coefficient	
		chapter 2	TREMOVE
LFC/quarterly GDP	LFC in €/km GDP in 10k €	−0,4585	−0,4585
Luggage space	0–1	0,08418	0,08418
Emissions	0–1	−0,06361	−0,06361
Range	100km	0,02220	0,02220
Acceleration	s	−0,04557	−0,04557
Diesel (small)		0,1939	−0,1
Diesel (medium|large)		0,1939	0,1939
LPG (small)		−0,05059	−0,4
LPG (medium|large)		−0,05059	−0,3
Battery		−0,04526	−0,04526
Large		−2,5105	−2,5105
quarterly GDP × large	10k €	1,738	1,738
λ_{ice}		0,8664	0,8664
λ_{fuel}		0,5952	0,5952
λ_{med}		0,1270	0,1270
λ_{lar}		0,1804	0,1804

higher than real world observations indicating that the stock share of retrofit LPG cars is probably limited to 1–1,5%. Aspects that have been excluded from the survey may imply a barrier to the choice for a LPG car, e.g. the retrofit operation as well as some other factors such as limited access to parking infrastructure. To bring simulations in line with observation we decided to adapt the dummy for LPG technologies to a value of −0,3 for medium and large engine sizes and a somewhat larger (absolute) value of −0,4 for small engine sizes.[2] This results in a baseline share for LPG cars of 1,1% in 2000.

The correction of the dummy for small diesel cars and LPG cars aims at bringing the model in line with observed choice behaviour. We note that these changes mainly affect the reference stock shares. In the simulation of an emission tax (see section 3.5), the lifetime cost coefficient plays a far more important role in the simulation of the technology shift, the value of this coefficient is not changed here.

3.2.2. Emissions

The TREMOVE Belgium model includes an emissions representation for road modes based on COPERT III methodology and some TREMOVE 2 extensions.

[2]The values for the LPG dummies were chosen to result in acceptable shares. It should be noted that accurate statistics on the LPG share in the stock seem difficult to obtain, different sources range from 0,5% to over 1,5%.

We here discuss the extension of the emissions model for the simulations of this chapter. A first extension concerns the alternative technologies which are not covered by COPERT III or TREMOVE 2. A second extension of the TREMOVE emissions module is more technical and relates to the necessity in this study to also calculate ex-ante emission data rather than the ex-post only used in previous simulations.[3]

Alternative technologies

The approach of this chapter in modelling emissions of alternative technologies is to start from the COPERT III framework which covers the conventional technologies.

The COPERT III methodology provides emission factors that are a function of the average speed. However, such detailed information seems not to be available for alternative technologies. In this section we will discuss the emissions modelling for the alternative technologies.

A short note on hybrids Although emissions as a function of average speed may differ when comparing hybrid to non-hybrid technologies, there seems to be no clear evidence on the exact relationship.

If we look at the existing diesel and gasoline (non-hybrid) technologies, we observe that their emissions profile is determined by mandatory European emission standards.[4] As the corresponding hybrid technologies are primarily promoted for their fuel efficiency record, it seems a reasonable assumption that these technologies will be tuned such as to optimise fuel efficiency given the mandatory emission standards which are identical for hybrids as for the non-hybrid technologies. Under such a setting the order of magnitude of emissions will not change, apart from those components such as CO_2 that are correlated to fuel efficiency.

Hence we decided to model emissions of hybrid technologies to be identical to the corresponding non-hybrid technology, except for fuel consumption related emissions.

CNG fuelled technologies For CNG technologies we use emission information from the MEET project. The MEET project (Hickman et al., 1999) provides emission correction factors for private cars running on CNG.[5] We decided

[3] *Ex-post* means in this context that we calculate emissions making use of the existing stock composition and modal transport activity. The *ex-ante* calculation assesses for a given year the emissions that new cars will emit over their entire expected lifetime.

[4] As of writing this chapter the Euro 4 standard applies.

[5] It may be argued that the application of a generic set of correction factors over distinctive emissions classes is a bit tentative. The approach is motivated by (Hickman et al., 1999) citing the limited amount of experimental data as main argument.

to apply these values to the emission factors of the corresponding gasoline technology (values are presented in table 3.2).

It is obvious that the values for VOC, NMVOC and CH_4 emissions are not independent.[6] In our implementation we decided to calculate VOC and NMVOC emissions by applying the corresponding factor, and calculate the emission levels of CH_4 as the difference between both components. It should be stressed that for our application the split of VOC emissions into different components is not of a major concern as we will apply a unique external cost coefficient for all VOC emissions.[7]

Hydrogen fuelled technologies The information available on emissions of hydrogen fuelled technologies is rather limited. We decided to use exhaust emission data from Markal by Vito (Katholieke Universiteit Leuven, Center for Economic Studies [CES KULeuven] and Vlaamse Instelling voor Technologisch Onderzoek [VITO], 2001).

The intrinsic specification of hydrogen technologies somehow results in a shift of exhaust emissions to fuel production related emissions. Although production of conventional fuels (diesel, gasoline, LPG) also results in some *life-cycle* emissions, these are considerably higher for hydrogen production as we assume here that hydrogen is produced through steam reforming of methane.[8] As we are studying the impact of technology shifts towards alternative technologies, we decided to include CO_2 emissions released in this steam reforming process in our model (see figure 3.3 for a comparison of CO_2 emissions by different technologies).

Appendix D provides the energetic efficiency for the hydrogen technologies. The calculation of the corresponding CO_2 emissions follows from the stoichiometric balance of the steam reforming process, assuming an efficiency

[6] VOC=NMVOC+CH_4

[7] See appendix C for the marginal external emission cost coefficients.

[8] According to Verbeiren et al. (2003) the CH_4 steam reforming process seems to be the most promising approach for the production of hydrogen.

Table 3.2. Emission correction factors for private car CNG technologies (source: Hickman et al. (1999); reference is a petrol car with TWC)

Pollutant	Factor
CO	0,383
VOC	1,810
NO_X	0,367
NMVOC	0,128
CH_4	9,452
C_6H_6	0,003

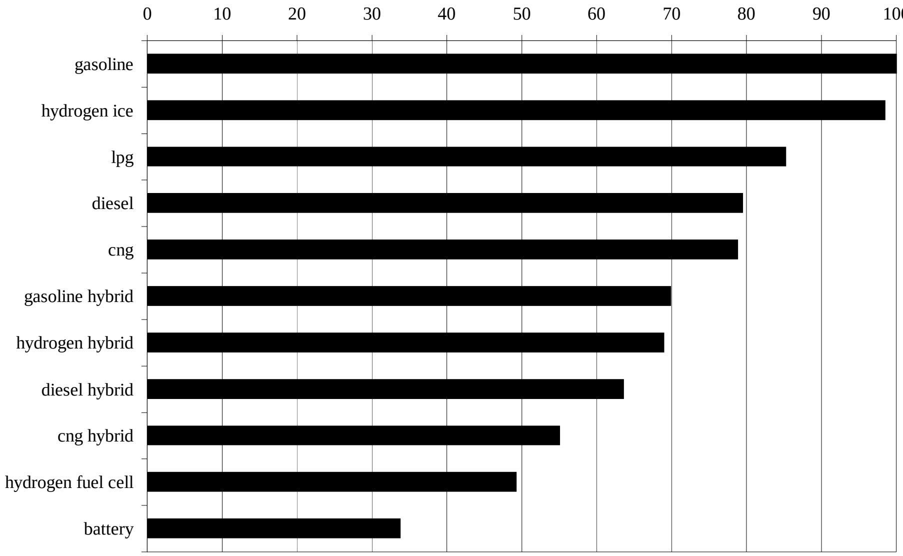


Figure 3.3. Baseline specific CO_2 emissions of new private cars with medium engine size in 2020 (index: gasoline level = 100)

for this process of 80% (based on Markal). We additionally assume 0,05g per kilometre emissions of NO_X by ICE technologies (based on Markal).

Battery cars Battery cars typically do not have any exhaust emissions. Similarly as for the hydrogen technologies, emissions are related to electricity production rather than consumption. To allow for a more or less consistent assessment of the environmental impact of a technology shift, we decided to include in our model emissions related to the production of the electrical energy used to charge the batteries. The factors for Belgium have been based on available country-specific data from the TREMOVE 2 model (G. De Ceuster et al., 2005).[9]

Ex-ante emissions

A last upgrade of the emissions model relates to the necessity to calculate ex-ante emissions for an emission tax simulation.

The TREMOVE model typically only calculates ex-post emissions: first the demand for passenger kilometres and the stock composition is calculated, and these results are fed in the emissions module which calculates the corresponding emissions (see figure 3.1).

[9]The emission factors for electricity production evolve over the modelling period, reflecting assumptions on the evolution of electricity production mainly based on the RAINS and PRIMES energy models (G. De Ceuster et al., 2005).

In our setup we however need ex-ante emissions of the different car technologies, as the upgraded private car technology choice model (see section 3.2.1) uses this information to calculate the stock composition. In our model for technology choice a variable that expresses the emissions level (relative to a conventional technology) is included. Furthermore in our simulation we will assess the impact of an emission tax on stock composition, for this we also need ex-ante emission calculations for the different technologies.

The ex-ante calculations use the same technology specific emission factors as the ex-post module. For every year in the modelling period ex-ante emissions are calculated for all available technologies. The emissions E_{ap} of pollutant p at vehicle age a are based on these emission factors and the expected annual mileage. The resulting emission cost is then calculated by multiplying E_{ap} by the external cost coefficient C_p of pollutant p.[10]

Ex-ante emission cost over the expected vehicle lifetime y are aggregated using a discounted total external cost approach based on Kolstad (2000) to calculate the ex-ante total expected emission cost EC of a new vehicle. To allow the comparison of technologies with different expected lifetimes, we finally calculate the external emission cost as an annuity over the vehicle lifetime that corresponds to the present value of the external emission cost.

$$EC = \frac{i}{1-(1+i)^{-y}} \sum_{a \leq y} \frac{\sum_p E_{ap} C_p}{(1+i)^a} \tag{3.1}$$

For the discount rate i we use the default TREMOVE value.

3.3. Alternative technologies

In this section we present our selection of alternative technologies and discuss how they enter the baseline scenario[11] in order to allow for a consistent simulation of an emission tax.

We start with an overview of the different fuels and their properties. In the second part of this section we have a closer look at the technologies.

We limit the discussion here to the selection of technologies present in our private car choice model (see figure 3.2).

The technology choice models (see section 3.2.1) are driven by cost data, functional car properties (e.g. luggage space), expected lifetime, mileage and GDP per inhabitant. Several sources have been used for the design of a baseline evolution (see section 3.4) for all of these variables; we limit ourselves here to an overview of the most important ones.

[10]In this section we make abstraction of the modelling year to avoid clutter in the notations. In the model both the emissions and the external emission cost factors evolve over the modelling period 1995–2020.

[11]Section 3.4 discusses the baseline.

Full details on the baseline evolution for alternative technologies (including fuels) can be found in appendix D.

3.3.1. Fuels

Conventional fuel properties have been based mainly on the International Energy Agency [IEA] (2003) for the base year fuel prices and taxes. The evolution of the ex-tax price[12] was based on the PRIMES-transport model (Knockaert, Van Regemorter, and Proost, 2002, we refer to the PRIMES-transport documentation for full details on the assumptions behind this evolution), the evolution of tax levels only accounts for the Cliquet excise tax increase implemented by the Belgian federal government (Federale Overheidsdienst, Kanselarij van de Eerste Minister, 2003).

Prices of alternative fuels have been based on FEBIAC (n.d.); Verbeiren et al. (2003); Vrije Universiteit Brussel, ETEC [VUB-ETEC] and Université Libre de Bruxelles, Centre d'Etudes Economiques et Sociales de l'Environnement [ULB-CEESE] (2001). Taxes on alternative fuels have been assumed identical to gasoline.[13] Full details on fuel cost evolution are provided in appendix D.

3.3.2. Technologies

The baseline evolution of private car technologies (both conventional and alternative) has been based on a broad range of sources, including TREMOVE 2, Verbeiren et al. (2003) and Vrije Universiteit Brussel, ETEC (2001). The expected lifetime and mileage per car data have been taken from the TRENDS project (see appendix C). The resulting lifetime costs are presented in figure 3.5 for medium engine size technologies.

Some attention has to be paid to the issue of the introduction date of the alternative technologies. The year that new technologies will leave the prototype stage and enter the market is very uncertain. After a first market entry it may again take several years before a technology becomes fully available with all manufacturers and car types. Many factors may speed up or slow down this process; several of them are beyond the scope of the TREMOVE modelling framework. This process can be described by the theoretical framework of experience curves as discussed by International Energy Agency [IEA] (2000). We want to stress that such a process is not included in the TREMOVE model. To summarise: in TREMOVE technologies are fully available or not available at all at a given point in time. This seems

[12] The ex-tax price is the resource cost (excl. taxes).

[13] There are no or only small existing excise taxes on LPG, CNG and electricity. As we assume hydrogen to be based on natural gas, we assumed they are freed from excises as well. However, this would imply an indirect subsidy for CNG, electric or hydrogen powered cars when they are introduced. For that reason, we implement an excise tax per unit of energy that is identical to gasoline.

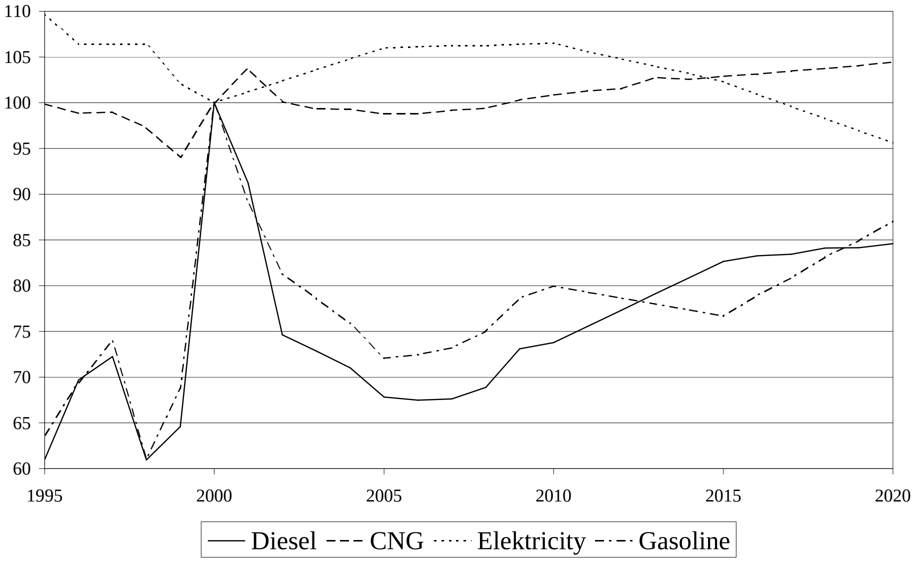


Figure 3.4. Baseline evolution of ex-tax fuel price for non-commercial use (index: 2000 level = 100

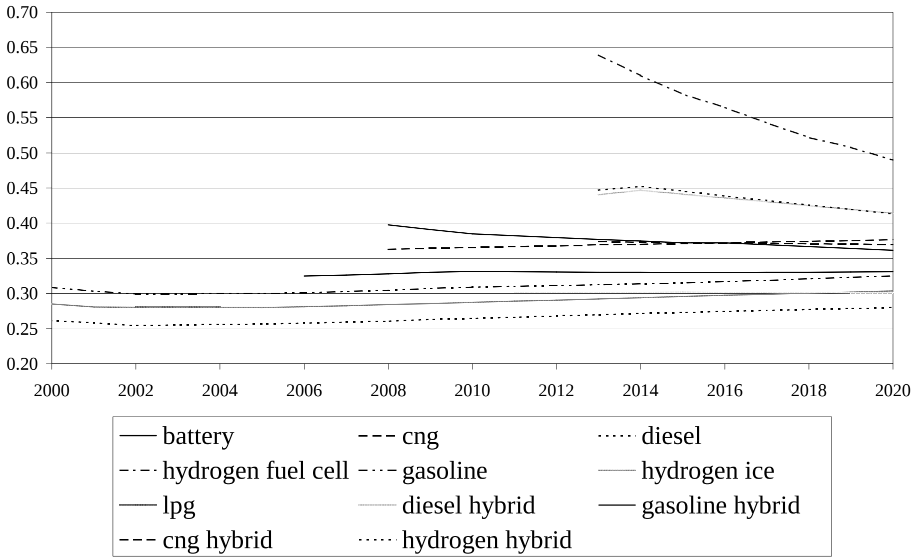


Figure 3.5. Baseline evolution of lifetime cost for private car technologies with medium engine size (in €/vkm)

not too bad an assumption for a long run model, the only disadvantage of this limitation is that it is not possible to simulate a shift of the introduction date depending on e.g. the number of units sold in the year before or efforts in research and development funded by the government.

That said, we need to fix an introduction date in TREMOVE for every alternative technology, and this date has to be the same in both the baseline and the environmental tax simulation. We have chosen to be rather optimistic on the full market availability of the different technologies (see table 3.3). This may be too optimistic, but here we should draw again the attention of the reader to the focus of this chapter: study whether a technological and/or modal shift can contribute to a reduction in emissions. In case pessimistic introduction dates were selected (e.g. 2019), not much shift between technologies could be simulated as the modelling period ends in 2020 and no stock turnover would happen. The option exists to shift the introduction date exogenously between the baseline and the environmental tax simulation. However, this would make abstraction of actual policy (unless one assumes the Belgian authorities would start producing the alternative cars themselves).

Baseline emissions of alternative technologies are modelled as described in section 3.2.2.

3.4. Reference scenario observations

A baseline scenario is implemented for the period 1995–2020. This *business-as-usual* scenario simulates what happens in a situation where no new policy measures are implemented apart from those already decided. The aim of the baseline is to function as a reference for the environmental tax simulation (see

Table 3.3. Assumed introduction year of private car technologies (loosely based on Verbeiren et al., 2003)

Technology	Size class	Introduction
Diesel conventional	small	2002
Diesel conventional	medium, big	1995
Gasoline conventional	*all*	1995
LPG (retrofit)	*all*	1995
CNG (retrofit)	*all*	2008
Hydrogen ICE	*all*	2013
Diesel hybrid	*all*	2011
Gasoline hybrid	*all*	2006
CNG hybrid (retrofit)	*all*	2013
Hydrogen ICE hybrid	*all*	2013
Battery	small, medium	2008
Hydrogen fuel cell	*all*	2013

section 3.5), to allow for a consistent assessment of the impact of the tax on technology shift, modal shift, emissions reduction and welfare cost.

This section discusses some aspects of the specification of the baseline scenario. For a more comprehensive discussion we refer to appendix C. Here we provide a summary overview of the baseline evolution for transport activity, vehicle stock composition and emissions.

3.4.1. Transport activity

The evolution of transport activity in the baseline scenario is exogenous to the model and is based on draft TREMOVE 2 specifications for Belgium. The activity level for the historical period has been brought in line with observations (European Commission Directorate-General for Energy and Transport [DG TREN], 2004). The baseline activity evolution is represented in figure 3.6 and figure 3.7.

3.4.2. Vehicle stock

The vehicle sales composition reflects the evolution in the properties of the different technologies. The share of alternative technologies increases over time as their lifetime costs are assumed to decrease. The sales composition for selected years is presented in figure 3.8.

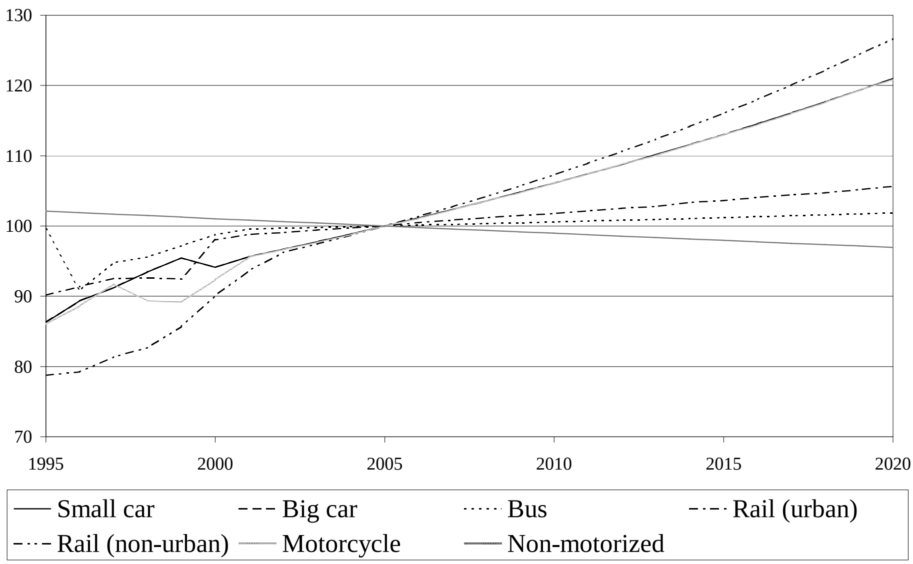


Figure 3.6. Baseline evolution of passenger transport activity demand in pkm (index: 2005 level = 100

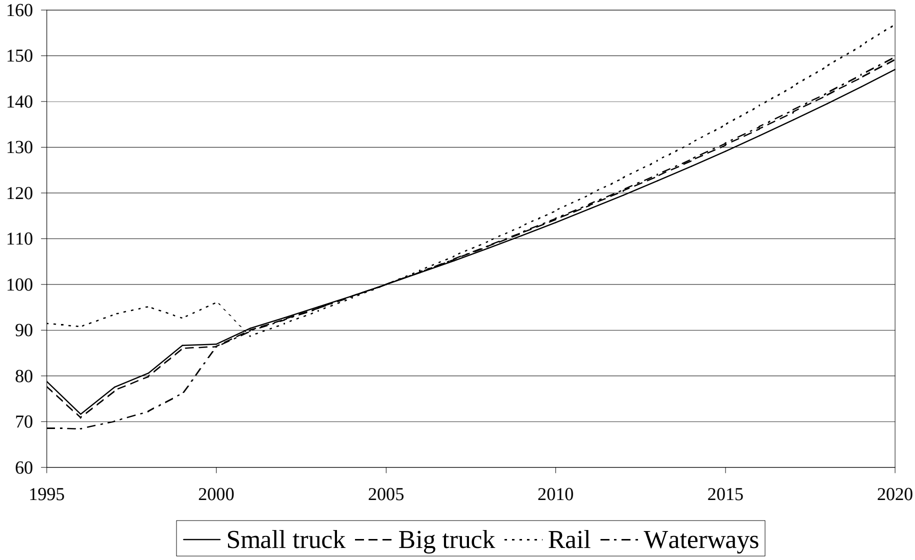


Figure 3.7. Baseline evolution of freight transport activity demand in tkm (index: 2005 level = 100

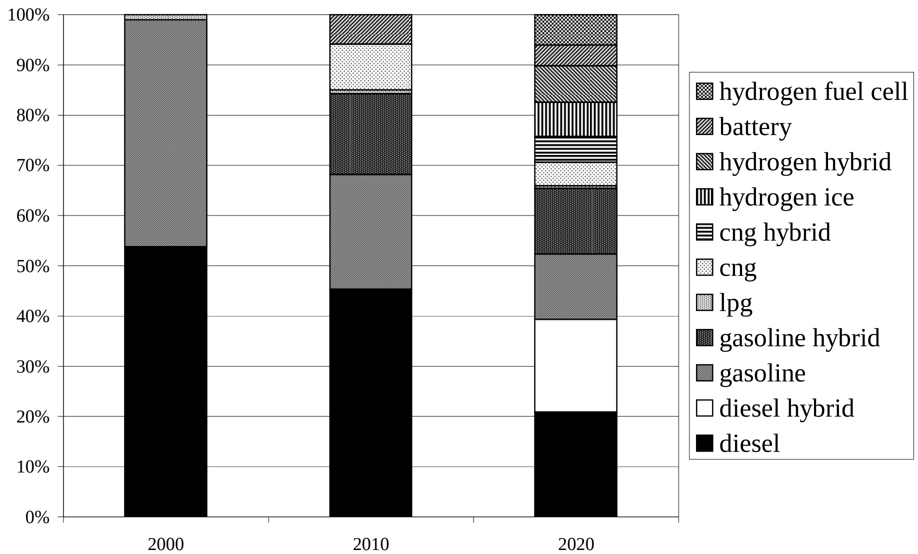


Figure 3.8. Baseline private car sales composition

We observe that alternative technologies enter the market rather effortless, considered that no supporting measures are included in the baseline.

The corresponding stock composition is provided in figure 3.9 for private cars. One may consider the simulated penetration of new technologies as rather optimistic. We should however not forget the market introduction assumptions made in the baseline scenario (see section 3.3.2), in order to allow for a consistent emission tax simulation.

3.4.3. Emissions and external costs

The results of the emissions module (see section 3.2.2) for the baseline are presented in figure 3.10. We see a decline in most regulated emissions, only for CO_2 there is an increase. The decrease is the sharpest for SO_2 emissions. The reason is that the more stringent fuel standards are reflected immediately in overall emissions whereas technology related emission reductions need stock turnover to become effective. As such the sharp decline in the beginning of the modelling period is mainly the result of technological improvements introduced before 1995.

Combining the data provided by the emissions module with the external cost coefficients (see appendix C) we can compare the average external emission cost[14] per passenger kilometre (pkm) or ton kilometre (tkm) for each

[14]More precisely it is the activity weighted average value of marginal external emission costs per passenger or ton kilometre. Marginal external costs of transport activity may for instance vary across technologies and vehicle ages used by the same mode.

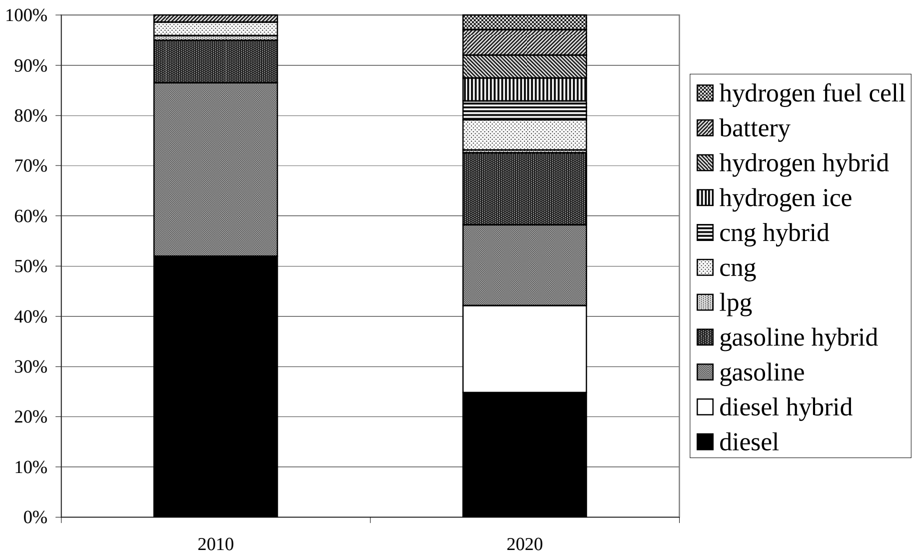


Figure 3.9. Baseline private car stock composition

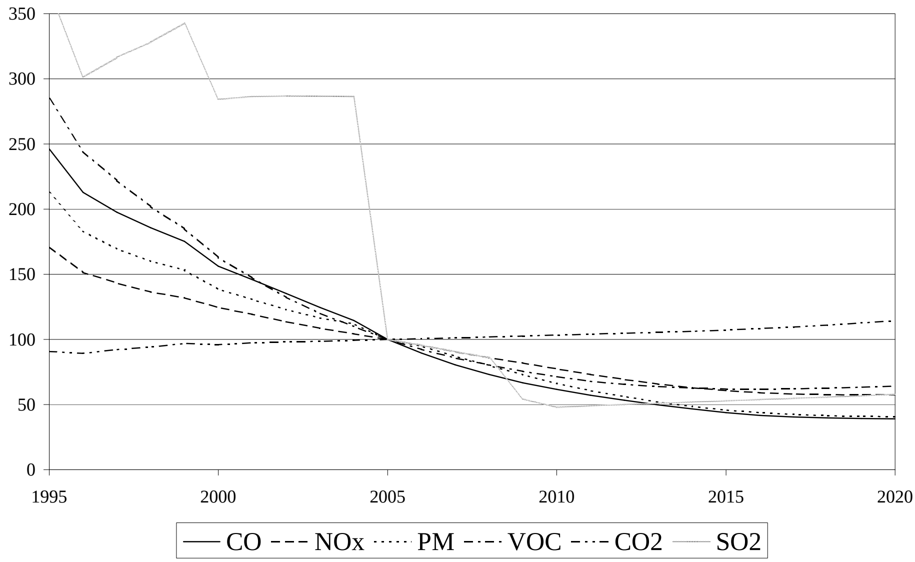


Figure 3.10. Baseline evolution of overall transport emissions (index: 2005 level = 100)

mode.[15] The results for the year 2020 are presented in figures 3.11 and 3.12.

The lower external cost for small cars is mainly a result of a lower share of diesel technologies in this class. Contrary to common opinion we observe buses not to be a more environmentally friendly mode. For passenger rail transport the picture differs between urban and non-urban, mainly because we assumed all urban rail transport to be electric.[16] For freight the external cost of the different modes in non-urban areas are in the same order of magnitude apart from light duty vehicles which are less environmentally friendly (mainly because of low load factors and rather loose emission standards for this category of vehicles).

The ex-ante data provided by the emissions module allow us to compare the external emission costs per vehicle kilometre (vkm) for new technologies (see figure 3.13).

We observe the alternative technologies to be cleaner than the conventional diesel and gasoline car. Especially the fuel cell hydrogen car seems to be a very environmentally friendly alternative. We want nevertheless to draw the attention of the reader to the overall order of magnitude of the emission

[15] Translating transport demand levels expressed in passenger or ton kilometre to vehicle activity expressed in vehicle kilometre (or inversely) is done using constant market-specific occupancy rates (or load factors) which are calibrated on an externally provided baseline scenario. We refer to appendix C for a discussion of the TREMOVE model structure.

[16] Note that we only consider external costs by emissions here, emissions-free nuclear electricity production has a rather large share in the Belgian electricity production.

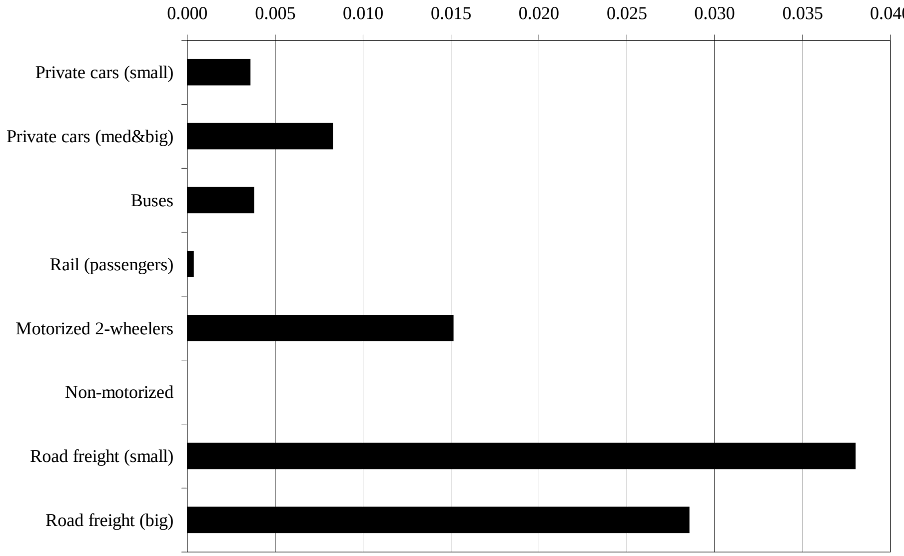


Figure 3.11. Baseline external emissions cost of modes in urban areas in 2020 (in €/pkm for passenger and €/tkm for freight transport activity)

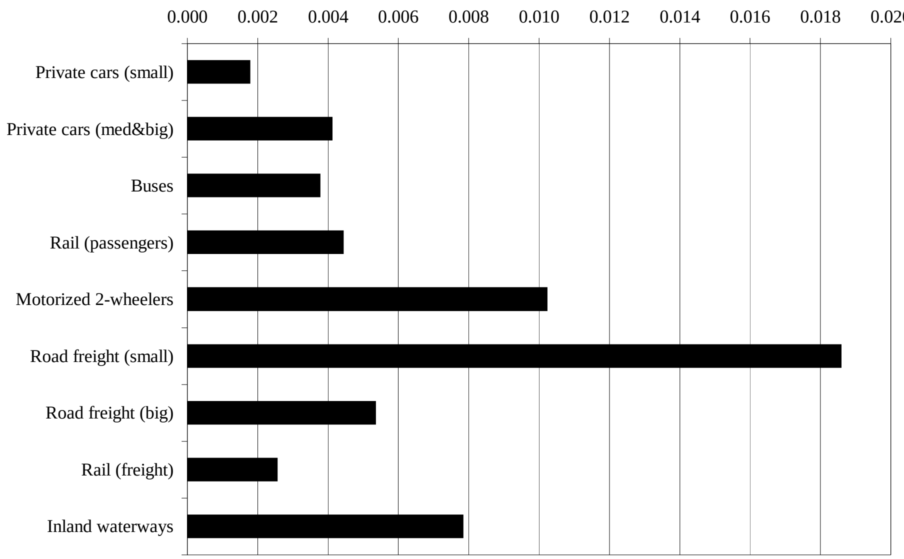


Figure 3.12. Baseline external emissions cost of modes in non-urban areas in 2020 (in €/pkm for passenger and €/tkm for freight transport activity)

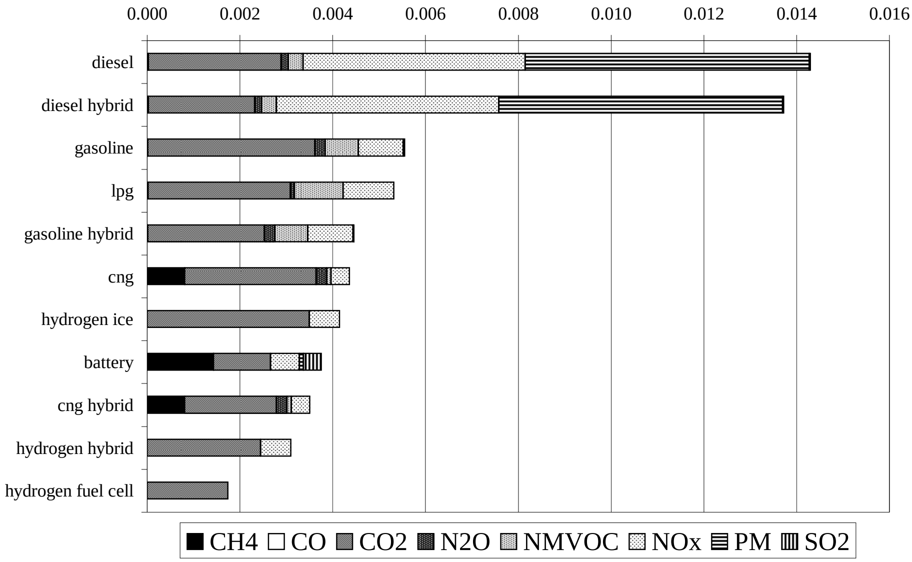


Figure 3.13. Baseline external emission impact of new private cars with medium engine size in 2020 (in €/vkm)

cost, which is even for conventional diesel and gasoline technologies[17] rather low. This is a result of the successive tightening of emission standards by the EU Commission, resulting in a major decrease of emissions. We present this evolution in figure 3.14. The decrease is convincing, and we should add that in the pre-'96 period already an impressive decrease was achieved, as is reflected in the overall emissions evolution presented in figure 3.10.

3.5. Simulating an emission tax

A reduction of emissions of a given pollutant can be obtained at the lowest social cost (excluding external effects) by levying the same tax per ton of emissions for all polluters (Kolstad, 2000). As we want to reduce external emission costs rather than the amount of emissions, the level of the tax has to be equal to the marginal external cost of the emissions C_p (per mass-unit of emission; see appendix C).

The emission tax we simulate is levied for all modes. For road modes the tax per kilometre differs according to technology, vehicle age and region (urban or non-urban) because external impact by emissions differs along these dimensions. We recall that we try to reduce the *external costs* by the pollutant

[17] The baseline conventional diesel and gasoline technologies in 2020 are Euro 4 cars running on sulphur free fuel. The Euro 4 standard is mandatory from mid-2005 on, sulphur free fuels enter the model in 2009.

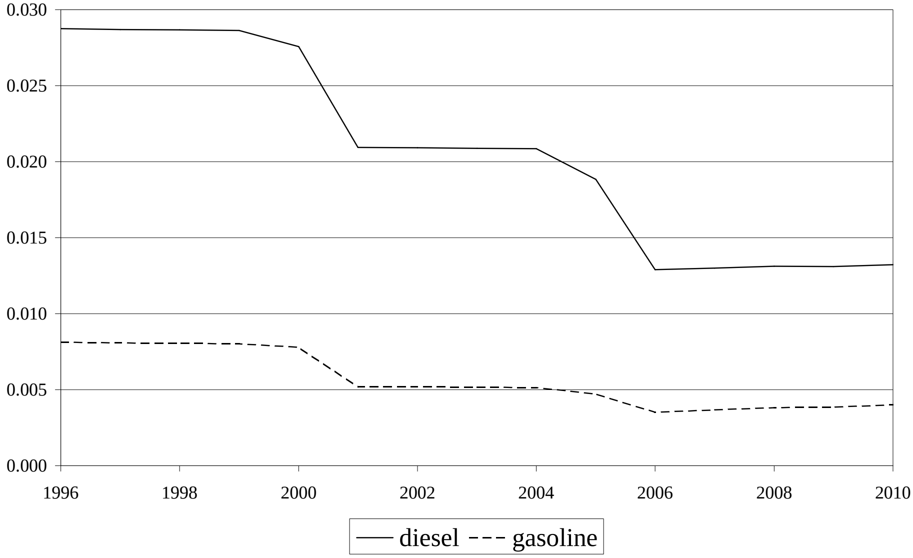


Figure 3.14. Baseline evolution of external emissions cost of new private cars with medium engine size for conventional technologies (in €/vkm)

rather than the *amount of mass* emitted. In the latter case the tax would have to be equal for all regions.

In our emission tax simulation, we expect to achieve two objectives. First, we will achieve a given emission reduction in each region at the lowest cost. Second, we will push the emission reduction up to the point where the marginal cost of one ton of extra emission abatement effort in the transport sector equals the marginal external emission cost that is avoided.

The emissions considered are tailpipe emissions only. The rationale behind this is that the remaining part of the life cycle emissions has to be addressed by measures targeting other activity sectors. However we added non-tailpipe emissions for some technologies/modes in order to allow for a more realistic emission tax simulation as discussed in section 3.2.2.

The tax income generated in the simulation is explicitly assumed to be used for reduction of labour taxes.[18]

In a first simulation we will average the taxation level of the different technologies in order to neutralise the existing differences in tax levels which are not environmentally motivated.

In a next step we will tax different pollutants at their marginal external cost. We assume here that the marginal external cost of each of the pollutants

[18]This assumption is reflected in the level of the marginal cost of public funds, which in our simulation amounts to 6,6% of the change in tax income. We refer to the introduction for an overview of the different cost components contributing to the welfare assessment.

is only a function of the emission level of that pollutant and the location of the polluter.[19]

3.5.1. Levelling the playing field

Before we look at the simulation of an emission tax we will in this section have a closer look to the existing taxes and study in how far they reflect differences in marginal external cost. The baseline figures for 2000 are provided in figure 3.15.

We observe that existing taxes do not reflect marginal external emissions cost by the different technologies. Taxation differences for different engine sizes may be based on non-environmental motivations (e.g. equity), but for the same engine size there seems not to be any ground on which a taxation difference could be motivated apart from external emission cost. We therefore decided to simulate in a first step a taxation scheme that levels differences over technologies of the same size class (and mode).

In this simulation we replace the existing taxes (from 2006 on) by a kilometre tax that amounts to the average tax level per vehicle kilometre (vkm) in the baseline scenario.

[19]Time (hour of the day, season) can also influence the level of the external emission cost but is not included in TREMOVE due to modelling framework limitations.

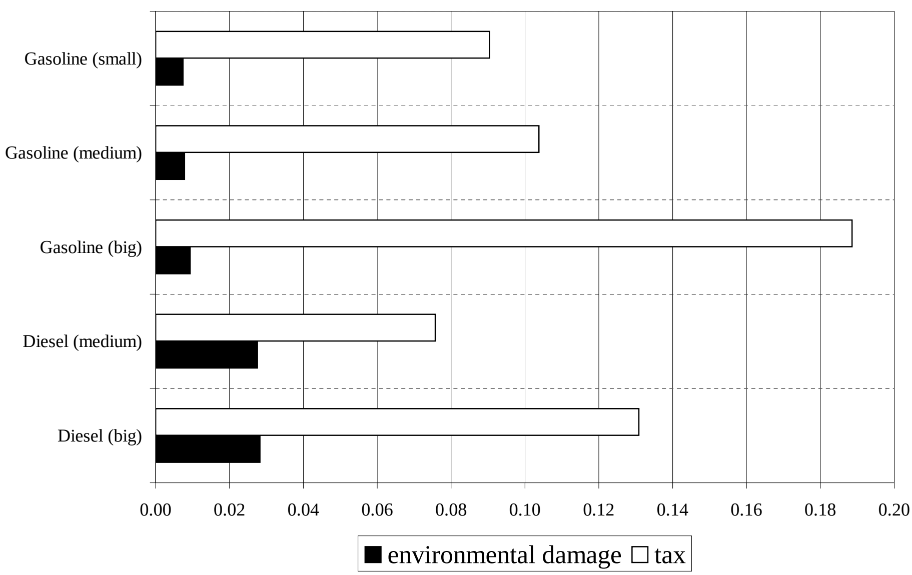


Figure 3.15. Baseline taxes compared to marginal external emission cost for new private cars in 2000 (in €/vkm)

The less taxed technologies lose market share as a result of this levelling of the playing field (see figure 3.16). Especially the share of diesel vehicles becomes smaller. We also observe a shift away from hybrid vehicles towards their conventional counterparts. This is mainly explained by the high fuel taxes in the baseline scenario which magnify the fuel efficiency difference.

For light duty freight vehicles (LDV, gross mass under 3,5 ton), we observe a rather big technology shift (5 to 10 percentage point share change) reflecting the higher price sensitivity assumed on this market (see appendix C). For motorised two-wheelers, no technology shift is observed as we do not change these taxes.

The corresponding change in emissions is presented in figure 3.17. Using the marginal external cost coefficients C_p (see appendix C) we calculate the emission cost reduction for every year in the modelling period. The 2005 present value of the annual external cost reductions is then added up, resulting in a net emission cost reduction.

We limit the discussion of the levelled tax simulation to the induced technology shifts and related emission changes as this is the only focus of this simulation. Small modal shifts do occur in the simulation but they do not provide much insight.[20]

The environmental gain observed in this simulation results from a change in the taxation policy such that it is environmentally neutral rather than promoting whatever technology for no apparent reason. Eliminating this distortionary tax should be feasible without a loss of consumer surplus, producer surplus and tax income. A net welfare gain (that includes an environmental gain) is therefore obtainable.

This levelled technology tax simulation provides a neutral comparison base that allows for a better understanding of subsequent environmental tax simulations that aim at a shift towards a cleaner technology stock composition.

3.5.2. Emission tax simulation

In this section we discuss the simulation of an emission tax. This simulation considers a tax on all emissions and the tax level is fixed at the marginal external emission cost level.[21]

The tax is levied from 2006 onwards on all technologies and modes, and the level (per mass unit) is identical for all vehicles but is differentiated over

[20] Ideally, the level of the tax should be chosen such that no modal shifts or overall change in transport demand is induced. However, the TREMOVE model does not allow for this kind of optimisation and therefore the baseline scenario tax level was used which does result in small changes in modal demand. This consideration also explains the small net shifts between technologies of different engine sizes.

[21] This simulation aims at setting the benchmark for efficiency by implementing a *first-best* scenario. A discussion on the role of the first best scenario in cost benefit assessment is provided in the introduction.

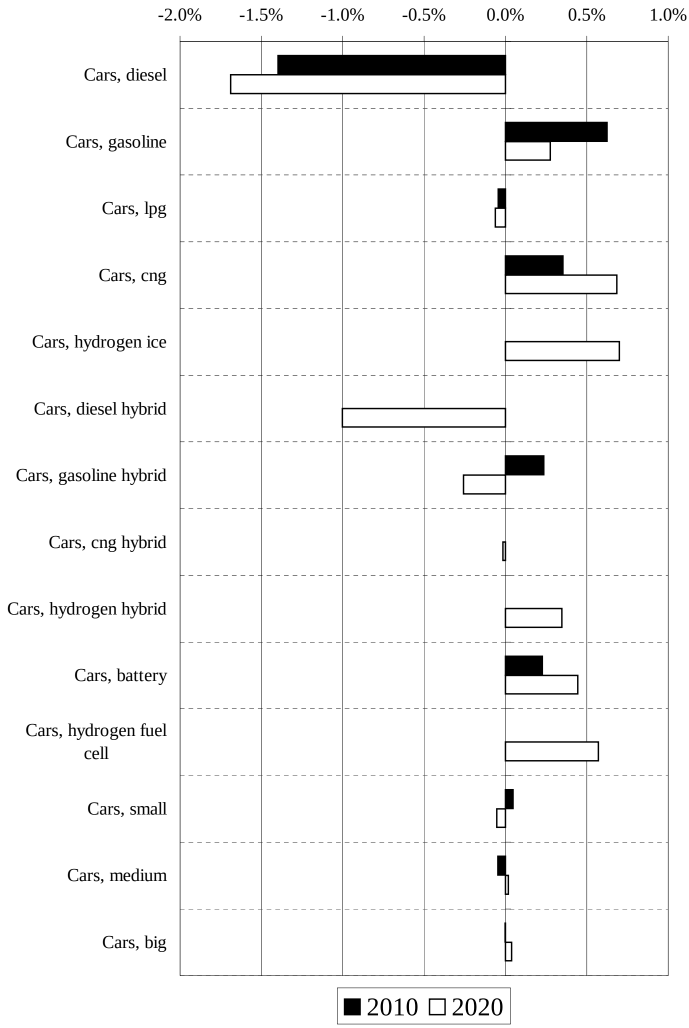


Figure 3.16. Impact of levelled tax on private car stock composition (change of technology share in percentage point compared to base case levels)

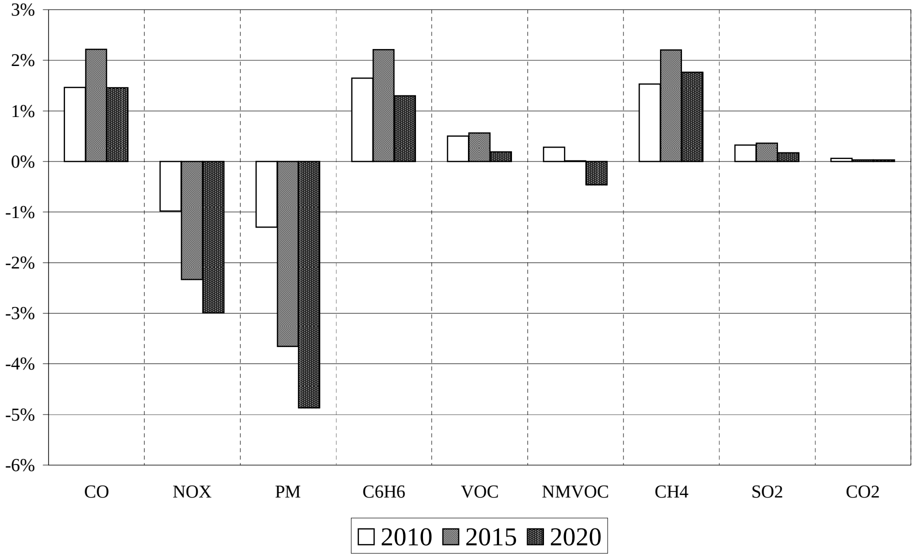


Figure 3.17. Impact of levelled tax on overall transport emissions (in % change compared to base case levels)

metropolitan (Brussels), other urban and non-urban areas.[22]

For particulate matter (PM), only diesel and electrical technologies are taxed, as there is too much uncertainty regarding the level of PM emissions for the other technologies.[23] COPERT III does not include PM emission factors for gasoline cars.[24]

The emission tax simulation is compared to the levelled tax simulation: the emission tax is added on top of the levelled tax. This way, the only tax difference between the technologies of the same mode and size reflects the marginal external cost of the pollutants considered. Hence, a realistic insight in the environmental potential of the different technologies can be obtained.

The generalised price variable is the main driver in the evolution of demand for transport activity. This composite cost variable covers all resource costs, taxes and time costs per passenger kilometre (pkm) or ton kilometre (tkm) and is calculated for all transport markets. A shift between modes as well as

[22]The exercise done her is strictly limited to the question of the impact of such a tax on transport activity and does not discuss the specifications of the technical implementation of the tax. It seems to us that it should be feasible technologically, but such a system may come at a considerable cost (which is *not* taken into account here) and there may also be issues related to privacy concerns.

[23]Lacking sufficiently detailed information on electricity production it is assumed in our model that electrical energy is produced in the area where it is consumed.

[24]In the case that we would have included PM emission factors for non-diesel technologies, the differences in emission tax between the technologies would be smaller and hence smaller technology shifts would result.

an increase or decrease in global transport activity results from any change in the generalised prices, which are presented in table 3.4.[25]

We observe that in the equilibrium the generalised user prices increase for most modes as a result of the emissions tax. Only for passenger rail is there a small decrease. The relatively favourable environmentally footprint of electric rail (which constitutes a large share in passenger rail activity) induces a modal shift upon the introduction of the emissions tax. This increase in rail demand leads to shorter waiting times, which in turn decrease the generalised user cost to a larger extent than the original emission tax increase.

The overall decrease in transport activity amounts to 3,0% for freight transport in 2020, for passenger transport a smaller decrease (0,5%) is observed (in 2020).

If we look to the urban area of Brussels (figure 3.18), we see mainly a move away from large cars towards small cars, buses and metro, which is in line with generalised price evolutions. For freight transport we observe a small shift from small trucks (LDV) towards bigger vehicles (HDV) in the long run (2020).

In the non-urban area (figure 3.19) the decrease in waterways activity is

[25]Note that in the initial equilibrium, prices may be wrong for the different modes because of other reasons than environment (subsidies, congestion, etc.)—so getting it right for external emission cost is *no* guarantee that it improves things. We will discuss this issue in the welfare assessment in section 3.5.3.

Table 3.4. Impact of emission tax on generalised prices in €2000 per pkm or tkm (in % change compared to the levelled tax simulation)

		2010	2015	2020
Urban	Small car	0,99%	0,82%	0,78%
	Large car	2,56%	2,01%	1,77%
	Bus	1,69%	0,78%	0,46%
	Metro and Train	−0,23%	−0,33%	−0,35%
	Moped & motorcycle	5,39%	4,11%	4,83%
	Non-motorised	0,02%	0,01%	0,01%
	Small truck	4,73%	3,31%	3,09%
	Big truck	8,80%	4,58%	3,82%
Non-urban	Small car	0,44%	0,43%	0,46%
	Large car	1,36%	1,17%	1,06%
	Bus	3,42%	2,23%	1,87%
	Train	3,03%	3,05%	3,72%
	Moped & motorcycle	4,81%	3,24%	3,97%
	Small truck	3,33%	2,43%	2,30%
	Big truck	7,89%	4,74%	4,28%
	Freight Train	2,44%	2,03%	1,80%
	Waterways	9,03%	8,05%	7,01%

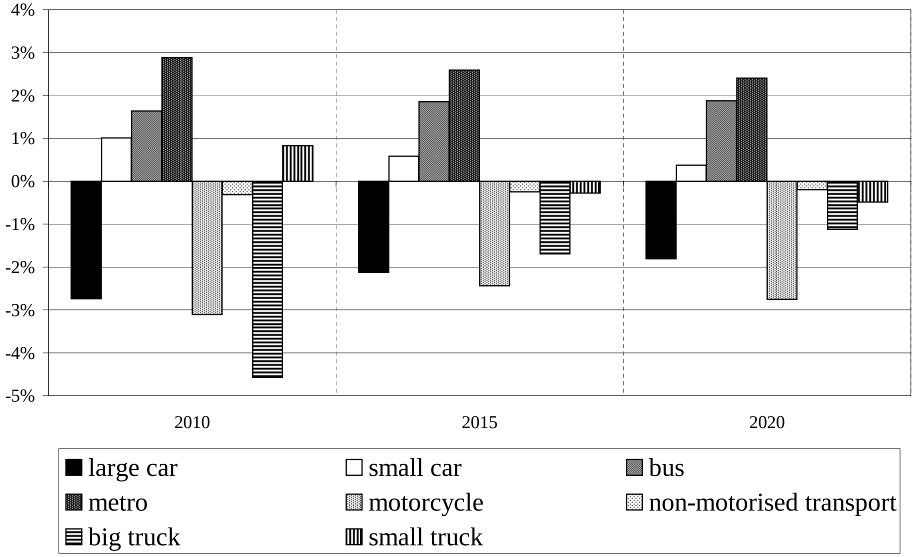


Figure 3.18. Impact of emission tax on passenger transport activity in Brussels (in % change compared to levelled tax simulation)

rather obvious (and reflecting the change in generalised price). The lower generalised cost of waterways transport combined with its rather bad environmental record (see figure 3.12) results in a higher relative impact of the emission tax compared to the other freight modes. For the other modes we observe similar shifts as for the Brussels area.

Freight train activity increases in the short run but this shift becomes smaller in the long run. This is the result of the evolving vehicle stocks for the road modes: in the short run one can only react to the new tax by a modal shift (and overall activity decrease), whereas in the longer run the stock composition changes as a function of the tax and modal shift becomes less important.

In the private car stock composition (figure 3.20) we observe the shift from diesel to gasoline and a smaller shift from conventional towards hybrid technologies. Gasoline vehicles produce less PM and NO_X emissions, whereas hybrid vehicles are more fuel efficient and hence emit less CO_2 compared to their conventional counterparts. Also some other technologies see an increase in their vehicle stock share.

For the light duty freight vehicles we see a shift from diesel to gasoline (see figure 3.21. This shift is bigger in percentage point compared to the private car shift, reflecting the assumptions made regarding price sensitivity (see section 3.2.1).

The change in fuel consumption (figure 3.22) shows a clear shift from

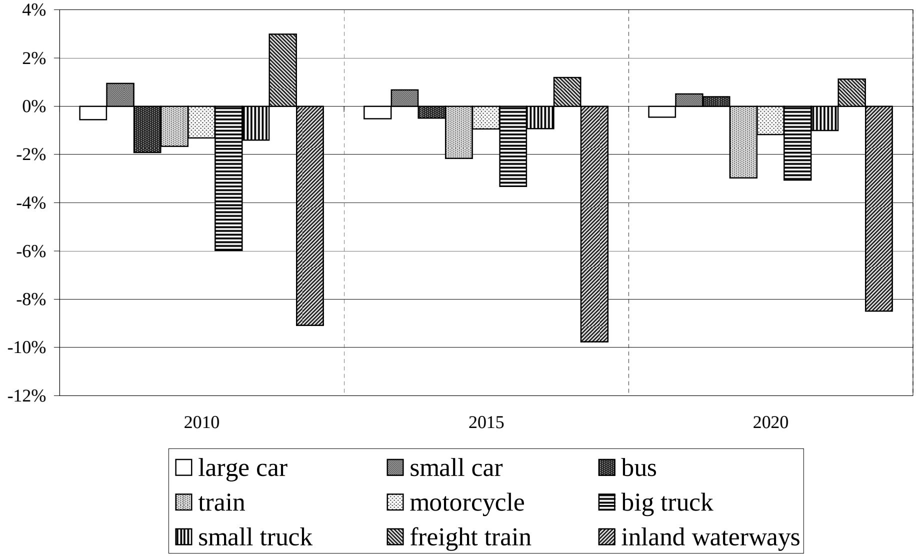


Figure 3.19. Impact of emission tax on passenger transport activity in non-urban areas (in % change compared to levelled tax simulation)

diesel to gasoline. Also the consumption of CNG increases, due to a shift towards CNG technologies (private cars). In absolute figures, this increase is however much smaller than the increase in gasoline demand.

Looking at the emissions (figure 3.23), we see a reduction of about 5% in the NO_X and PM emissions. For CO_2 the reduction is smaller (about 2%). For CO and benzene emission we observe an increase, resulting from the shift to gasoline technologies.

An important reduction for SO_2 emissions is obtained. This is a result of the reduction in inland waterways activity, where less stringent fuel standards apply compared to road modes.

For completeness we add here that some measures which fall beyond the scope of our study can change the picture for conventional technologies. The baseline technological evolution for inland waterways transport was not allowed to change under the emissions tax, although one could imagine a switch to cleaner (low sulphur content) fuels in order to reduce the external emission cost. In a similar way we did not consider further improvements of conventional diesel private car technologies, although the EU Commission is preparing for Euro 5 standards as of writing this chapter.

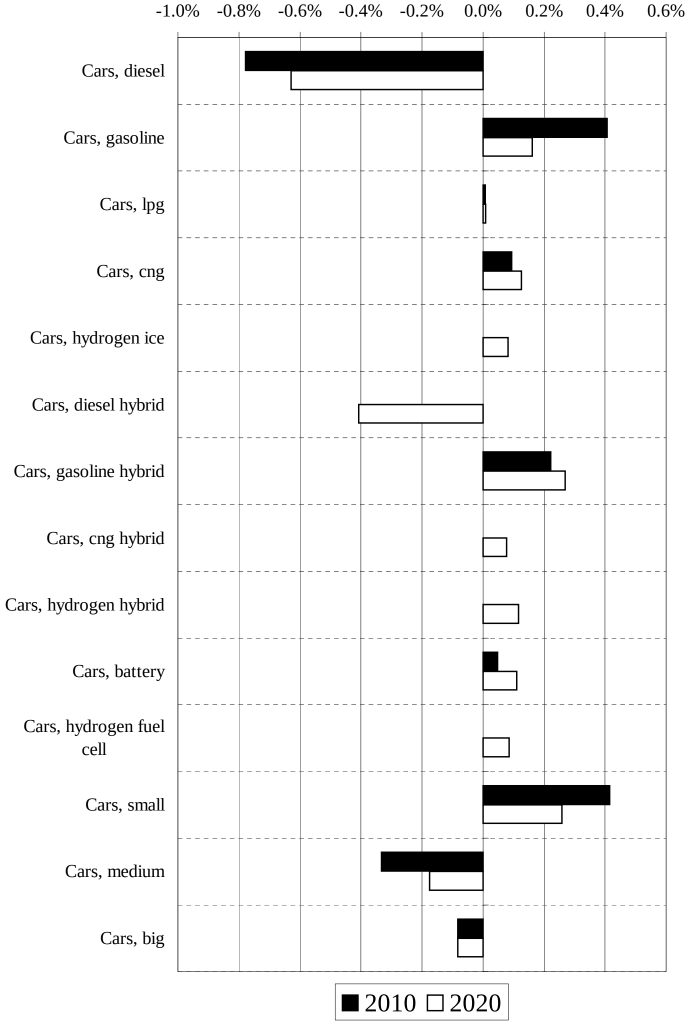


Figure 3.20. Impact of emission tax on private car stock composition (change of technology share in percentage point compared to levelled tax simulation)

Figure 3.21. Impact of emission tax on vehicle stock composition for LDV, buses and motorcycles (change of technology share in percentage point compared to levelled tax simulation)

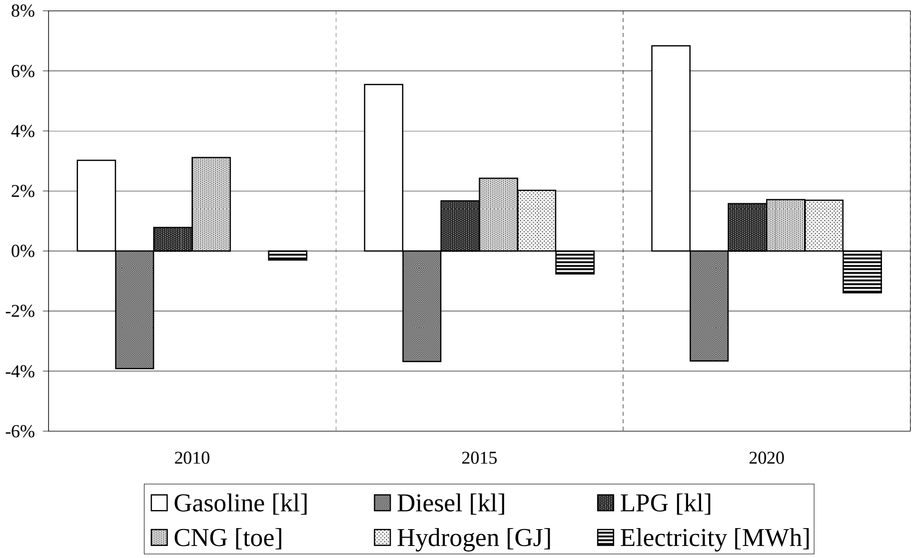


Figure 3.22. Impact of emission tax on total fuel consumption (in % change compared to levelled tax simulation)

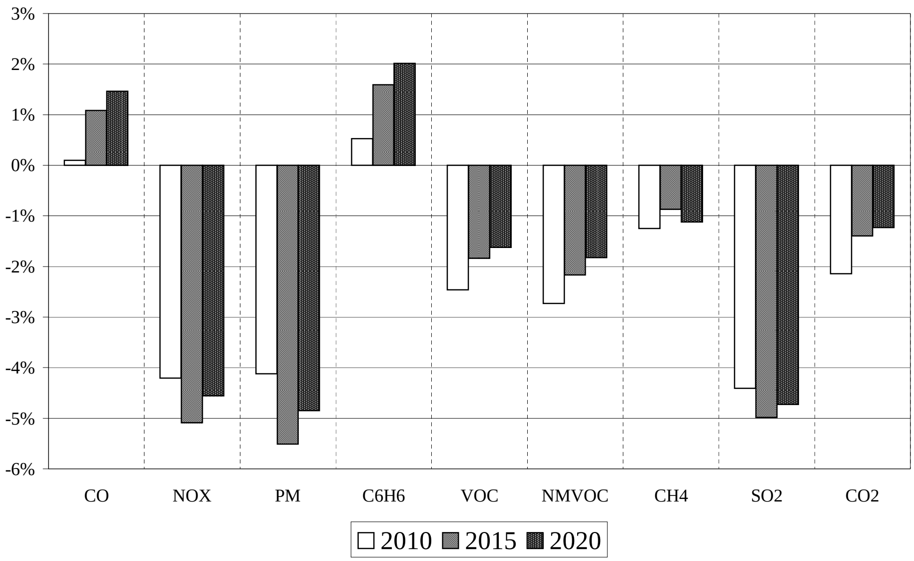


Figure 3.23. Impact of emission tax on overall transport emissions (in % change compared to levelled tax simulation)

3.5.3. Welfare assessment

In this section we study the overall welfare impact of the emission tax simulation by calculating its social cost.[26] In a first step we look at the cost to consumers, in a next step we include the external costs.

The breakdown of the annual cost to society (figure 3.24) of the emission tax scenario shows a net gain over the entire modelling period (all costs are expressed in €2000). There is a net cost faced by both consumers and freight transport, but the increase in income for the government is nearly as big. The MCPF term (marginal cost of public funds) represents the efficiency gain of lowering labour taxes through a shift of taxes (via higher transport taxes) to non-labour income taxes.[27]

Next, we have a look at changes in external costs resulting from the change emissions (figure 3.24). We see that for the emission tax simulation this cost is negative, hence it is a gain.

Here it is interesting to have a closer look at the determinants of the environmental gain by the reduction in emissions. The global decrease of activity contributes to about 65% of the environmental gain in the short run

[26]The definition of the different cost components contributing to the social costs of a scenario is discussed in the introduction.

[27]We assume that there are also other sources of income that are taxed but that only taxes on labour income are reduced.

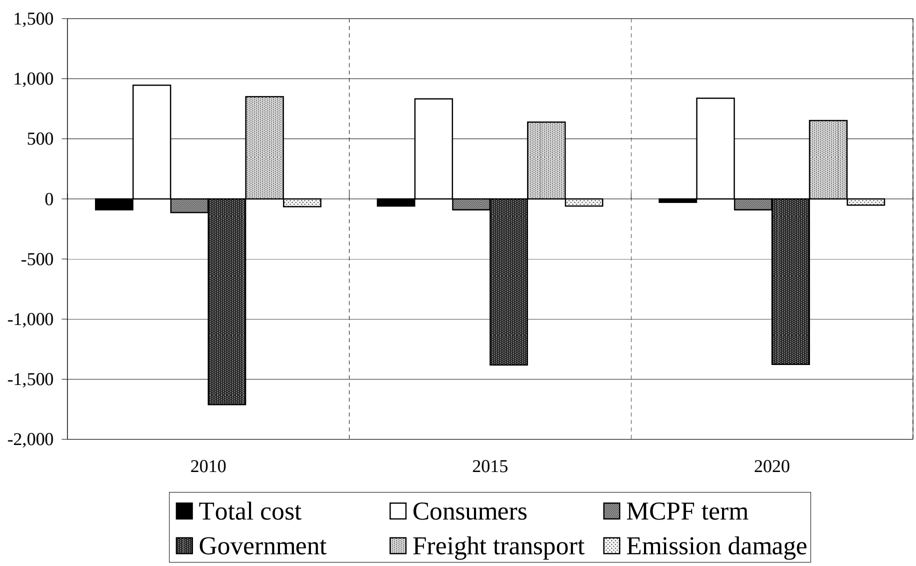


Figure 3.24. Annual welfare cost of emission tax in million euro compared to levelled tax simulation—positive values represent a social cost whereas negative values are a benefit

(2010). With the technological shift, the attainable environmental gain goes up to 90%, the remaining 10% being a result of a modal shift. In the long run (2020) we observe a smaller contribution of global activity decrease (45,9%), whereas adding the technology shift results in 92,4% of environmental benefits. In the long run, only 7,6% is contributed by a modal shift.

This result indicates that modal shift does not contribute much to a cost efficient reduction of external costs from emissions. The major contribution comes from a technological shift. As the technology stock turnover takes some time, in the short run a larger contribution from a global activity decrease is observed.

Finally we calculate for the emission tax simulation the 2005 net present value of the emission tax compared to the levelled tax simulation. Excluding external emission costs, the emission tax has a 2005 net present value of −162 million euro, which is a social gain. Adding the change in external emission costs further decreases the net present value to −809 million euro.

3.6. Conclusions

The TREMOVE Belgium model was selected as tool for the assessment of the environmental and social impact of reducing emissions in the transport sector. We successfully implemented important extensions to the model in order to allow for a comprehensive simulation of the impact of an emissions tax on transport activity and vehicle stock composition.

The baseline scenario suggests that a market exists for alternative technologies. It further indicates that existing taxes are distortionary as they promote less environmental friendly technologies. An elimination of these taxes results in a technological shift to gasoline technologies and provides an environmental as well as a net welfare gain.

An emission tax guarantees that a reduction in external emission costs is obtained in the most cost-efficient way considered that as a result abatement costs are equal on all markets. We observe that under such a context the major contribution to emission cost reduction comes from a technology shift rather than a modal shift. The overall welfare result is a net gain. The technology shift is again in the first place towards gasoline vehicles.

The absolute figures are however not tremendous, considered that existing conventional technologies are already rather clean as a result of past technological improvements. In the long run, private car transport may become as clean as public transport, an observation that we will study more closely in chapter 5.

CHAPTER 4

The welfare cost of more fuel efficient cars

4.1. Introduction

Concerns on climate change have urged policy makers to develop a strategy to reduce greenhouse gasses. The transport sector is a major contributor to these emissions and hence receives much focus in the debate on where emission cuts have to be realised.

The call for more fuel efficient private cars seems to have reached the EU Commission who put forward the ambitious target of reaching an average 120 g/km of CO_2 emissions by 2012 for new cars sold in the EU. There is however no free lunch: more efficient cars come at a higher (purchase) cost.

Research on the impact of fuel efficiency on technological production costs has come up with cost curves that are based on engineering estimates of efficiency enhancing technological improvements. P. ten Brink et al. (2005) present retail price increase as a function of a reduction in per kilometre CO_2 emissions (which are heavily correlated with fuel efficiency). The purchase cost curves are further detailed to account for car engine size and fuel. Other examples of this direct approach are National Research Council [NRC] (2002) and DeCicco and Ross (1996) who study an improvement in fuel efficiency and the corresponding retail price increase for the US private car market.

The link between fuel cost and fuel efficiency is researched in different studies in the field of econometrics. Different estimates for the fuel price elasticity of fuel efficiency have been presented, some examples include Johansson and Schipper (1997) and Small and Van Dender (2006). As noted by Small and Van Dender (2006), this elasticity can be calculated from the fuel price elasticities of fuel consumption and traffic level, for which an extended set of estimations can be found in past research. Goodwin (1992) provides a review of the topic.

A qualitatively comparison of fuel efficiency policies in the EU and Japan has been presented by Plotkin (2001). Simulations of policy scenarios to improve fuel efficiency have been limited so far to modelling the impact on new car sales only. COWI A/S (2002) discusses different fiscal measures and assesses their impact on car sales, CO_2 emissions and tax revenues for the government. P. ten Brink et al. (2005) use the estimated cost curves (see above) to compare the welfare impact of different implementations of corporate average fuel economy standards.

In our approach to the topic we will start from the link between fuel cost and fuel efficiency and develop an indirect methodology based on assumptions on consumer and supplier behaviour in order to relate fuel efficiency to overall car user cost.

Integrating our methodology in the TREMOVE transport modelling framework for Belgium allows for a comprehensive simulation of fuel efficiency policy and its impact on welfare and environment. In contrast to earlier research our model includes a representation of the entire vehicle stock composition and covers all transport markets. This allows for the simulation of policy measures that go beyond new vehicle sales and also target the existing stock or other modes (such as a CO_2 emission tax).

Comparing the EU policy of an average new car efficiency standard to an emission tax on all private cars, we reveal that a tax has a smaller welfare cost. This is in line with the intuition: an emission tax guarantees that emissions are reduced at the lowest cost for society (Kolstad, 2000, see section 3.5).

The social cost of a reduction in CO_2 emissions from private cars is however much higher than the corresponding reduction in external emission costs, even under the CO_2 emission tax scenario. Again this is a finding in line with intuition considering that the existing fuel taxes are already above the level of the corresponding external CO_2 emission costs.

In the first section we present the methodology and compare it to the literature. The second section assesses EU policy on private car fuel efficiency and a third section looks to a next policy horizon. In a fourth section we identify some limitations to our methodology and in a last section we draw some conclusions.

4.2. Modelling fuel efficiency

In this section we propose a methodology to assess the environmental and welfare impact of fuel efficiency. We proceed in four steps.

First we discuss two methods to relate fuel efficiency and user cost at the level of the individual vehicle. Two approaches are compared: a direct method based on engineering estimates of production costs and an indirect approach based on assumptions on consumer and supplier behaviour. Second we have a closer look into autonomous progress in fuel efficiency that is made over time. Third we compare test cycle to real world fuel consumption. Fourth we discuss how we can integrate these findings in the TREMOVE partial equilibrium model.

4.2.1. Direct or indirect cost curves

Methodology

To calculate the impact of improved fuel efficiency on the user cost, basically two approaches are possible.

The *direct* approach considers bundles of fuel efficiency enhancing technologies and links them to engineering estimates of the corresponding production cost. Such an approach is applied by P. ten Brink et al. (2005), providing retail price functions for different engine size classes. These functions express the purchase cost increase as a function of reduction in specific CO_2 emissions[1]. DeCicco and Ross (1996); NRC (2002) study an improvement in fuel efficiency and the corresponding retail cost increase for the US private car market (including light trucks).

The *indirect* approach considers the market outcome to link fuel efficiency to an increase in user cost. Two assumptions are used: one on consumer behaviour and one on the behaviour of suppliers. The basic assumption for *the consumer* is that he chooses between vehicle technologies based on the total user cost of each technology. This user cost variable is function of all monetary resource costs and taxes over the vehicle lifetime: fuel cost, purchase cost, repair and maintenance cost etc.

The second assumption in the indirect methodology is that, in a competitive market and for a given fuel price p, *car manufacturers* offer cars that have an optimised user cost with respect to fuel intensity[2]: if a manufacturer can produce a car with a lower user cost by changing the fuel intensity, he will do it.[3] We express here the user cost UC per vehicle kilometre as the sum of a resource cost (and tax) $RC(f)$ and fuel costs (including tax):

$$UC = RC(f) + f \cdot p \tag{4.1}$$

with f the fuel intensity and p the volumetric fuel price (including taxes).

[1]Throughout this chapter we use the expression *specific emissions* to indicate the per vehicle kilometre (vkm) emissions of an individual private car.

[2]Throughout this chapter we use the expression *fuel intensity* to indicate the volumetric fuel consumption per vehicle kilometre. A decrease of the fuel intensity corresponds to an improvement of fuel efficiency.

[3]It is suggested that the car market is oligopolistic. This may result in fuel efficiency decisions that depart from the assumption made here that competitive car manufacturers offer fuel intensity optimised cars. In section 4.5 we will discuss a number of caveats of the approach applied in this chapter.

Optimising the user cost UC gives:

$$\frac{dUC}{df} = 0 \Rightarrow \frac{dRC}{df} = -p \tag{4.2}$$

We can now calculate the resource cost $\Delta RC(f)$ resulting from a change in fuel intensity from f_0 to f:

$$\Delta RC(f) = \int_{f_0}^{f} -p\, df \tag{4.3}$$

The relation between the fuel price p and the fuel intensity f is captured by the elasticity ϵ of fuel efficiency with respect to fuel price, which is a result of the technology of firms:

$$\epsilon = \frac{df/f}{dp/p} = \frac{df}{dp}\frac{p}{f} \Rightarrow f = f_0 \cdot e^{\epsilon \ln(p/p_0)} \tag{4.4}$$

with f_0 the fuel intensity and p_0 the fuel price in a reference situation.

Substituting relation (4.4) in (4.3) and solving the integral provides us with an expression for the increase in resource cost $\Delta RC(f)$ as a function of the increased fuel intensity f:

$$\Delta RC(f) = \frac{p_0 \cdot f_0}{1 + 1/\epsilon}\left[1 - \left(\frac{f}{f_0}\right)^{1+1/\epsilon}\right] \tag{4.5}$$

Whereas for the direct approach there is a need for engineering estimates of production costs (and assumptions on the link between production costs and retail price), we need for the indirect approach estimates of the technological parameter ϵ (property of cost and production functions). We will come back to this issue in the next section where we compare both approaches.

Illustration

In this section we compare the cost of fuel intensity using the indirect and the direct approach. To allow for an integration of the methodology in the TREMOVE modelling framework (see section 4.2.4), we here analyse the test cycle fuel intensity of a vehicle with a given engine size. An overview of diesel and gasoline private car technologies included in TREMOVE is provided in table 4.1.

To apply the indirect approach, we need a value for the fuel price elasticity of fuel intensity ϵ. Johansson and Schipper (1997) estimated a value of about $-0{,}4$ for the mean fuel intensity of the car stock. Values provided by Goodwin (1992) for the long run petrol price elasticities of fuel consumption (about $-0{,}7$) and traffic level ($-0{,}3$ to $-0{,}5$) imply a value for ϵ in the range $-0{,}4$ to

Table 4.1. TREMOVE private car technology classes

Category	Fuel	Engine size	Availability
small diesel	diesel	<1,4 l	2002–2020
medium diesel	diesel	1,4–2,0 l	1995–2020
big diesel	diesel	>2,0 l	1995–2020
small gasoline	gasoline	<1,4 l	1995–2020
medium gasoline	gasoline	1,4–2,0 l	1995–2020
big gasoline	gasoline	>2,0 l	1995–2020

$-0{,}6$.[4] A more recent estimate is provided by Small and Van Dender (2006), presenting a value of about $-0{,}2$ for ϵ. Brons (2006) conducted a meta-analysis on fuel price elasticities and suggests a value of $-0, 22$ for the elasticity of fuel efficiency with respect to gasoline price. We decided to use the value of $-0{,}2$ for ϵ in this chapter.[5]

Purchase cost functions for the direct approach are based on P. ten Brink et al. (2005) for the different TREMOVE private car classes. The cost functions represent (packages of) fuel efficiency technologies most promising/likely to be applied in the period 2002–2012 and relate an increase in purchase cost (inclusive of taxes) to a reduction in specific CO_2 emissions in gram per kilometre compared tot 2002 base year data. As CO_2 emissions are proportionally to fuel intensity we can (using base year specific CO_2 emissions) easily convert them to a relative increase in fuel intensity.

The indirect approach is implemented by applying formula (4.5) using the same 2002 base year data. The obtained increase in per kilometre resource cost has to be translated to a corresponding increase in purchase cost to compare it to the direct approach. We here used the cost formula implemented in TREMOVE Belgium (see appendix C) where an increase in purchase cost results in an increase in repair and maintenance costs as well as an increase in insurance costs. All these costs are converted to an annuity over the expected vehicle lifetime,[6] and finally divided by the expected annual mileage to obtain a per kilometre cost increase.[7]

The direct and indirect approach for medium and big diesel technologies is presented in figures 4.1 and 4.2. Whereas for smaller improvements in fuel efficiency the cost increase simulated by the indirect methodology is clearly higher than with the direct methodology, the difference (nearly) disappears

[4]Small and Van Dender (2006) provide the expression for the relationship between the elasticities.

[5]We here assume a constant value for ϵ over the entire modelling period (1995–2020) for all engine sizes, fuels, and all values of fuel intensity.

[6]The TREMOVE model assumes that a private car buyer makes a rational decision in trading off the different cost components. We refer to chapter 2 for a discussion of this assumption.

[7]We here assume a discount rate of 4%, an expected lifetime of 9,5 years and an expected annual mileage of 13 475 km.

for larger increases.

For the small diesel class the difference is larger (see figure 4.3), but this may be related to the fact that this vehicle class is rather new making an application of the direct methodology less straightforward. On the other hand, the parameter ϵ for the indirect approach may differ over vehicle sizes, an aspect that we have not taken into consideration here, mainly due to a lack of evidence on the qualitative aspects of such a differentiation.

For gasoline cars, the difference between both methodologies is rather large, especially for medium and big sized engines (see figures 4.4, 4.5 and 4.6).

Given the large difference between both approaches, it is appropriate to have a more detailed look to the different assumptions behind both approaches. The direct approach presented by P. ten Brink et al. (2005) covers technological innovation over an entire decade. It looks forward to 2012 and compares the forecast availability of fuel efficiency technologies to a reference situation in 2002. As such, it allows for the inclusion of technologies with a negative user cost impact: these are technologies that are (implicitly) expected to make it to the market regardless of supporting policy measures.

The indirect approach however expresses how the user cost is optimised with respect to fuel efficiency at a given point in time. In the indirect approach the reference point is hence explicitly allowed to shift over time. It is here that the technologies with a negative net user cost fit in the indirect approach: the reference average new car becomes more fuel efficient over time at the rate

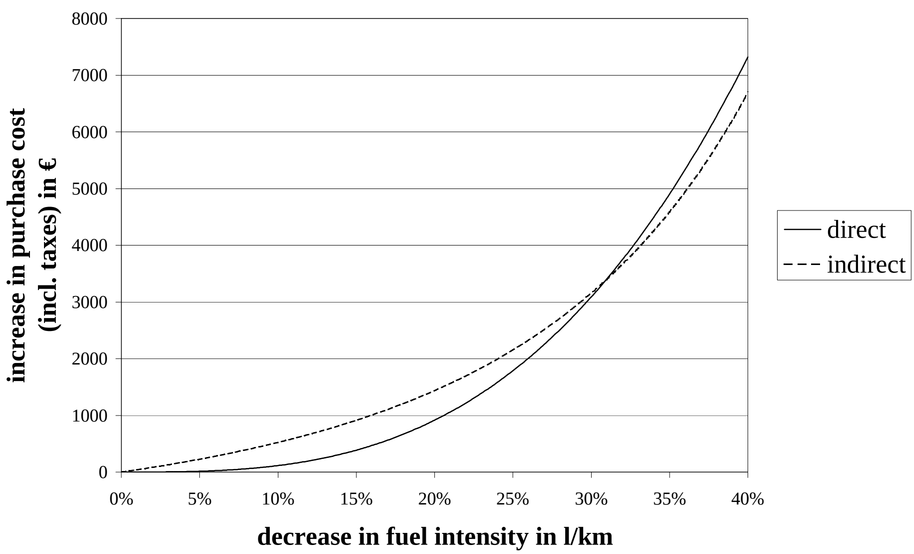


Figure 4.1. Cost of fuel efficiency for medium diesel cars (1,4–2,0 l)

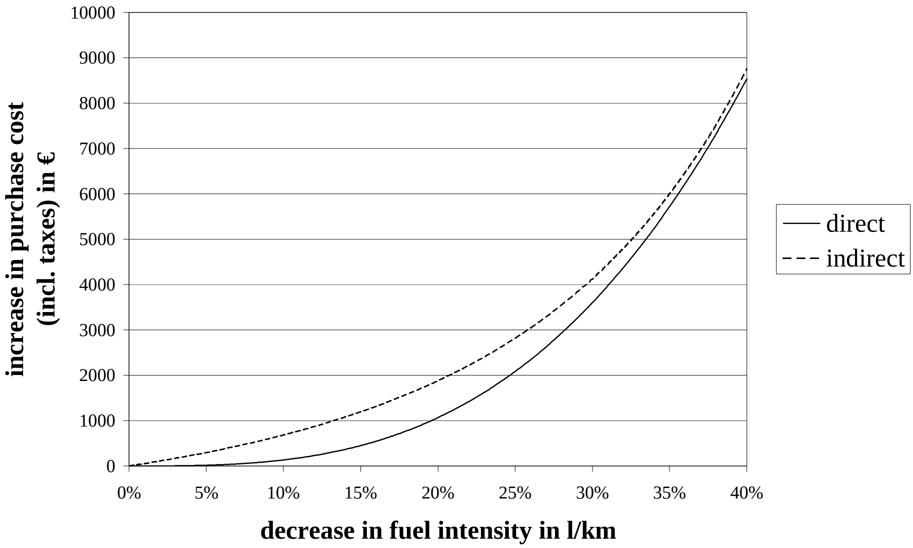


Figure 4.2. Cost of fuel efficiency for big diesel cars (>2,0 l)

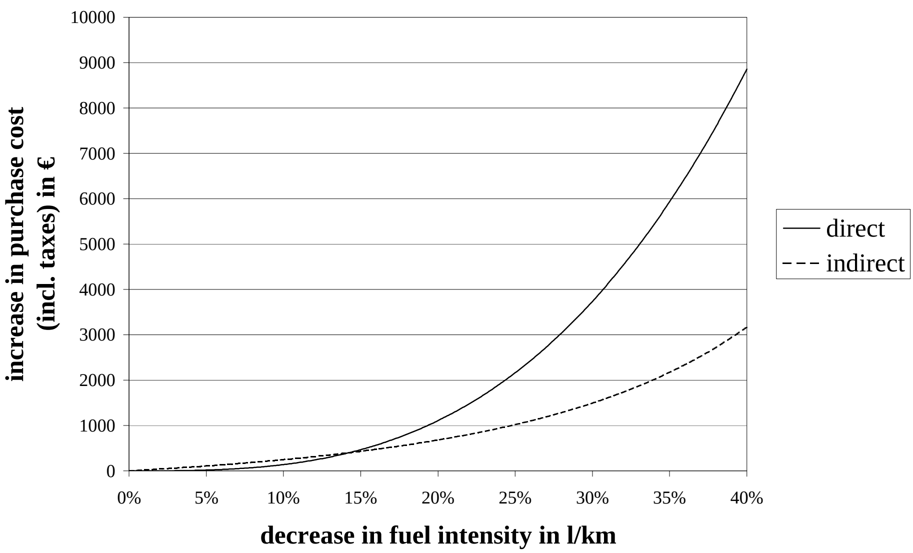


Figure 4.3. Cost of fuel efficiency for small diesel cars (<1,4 l)

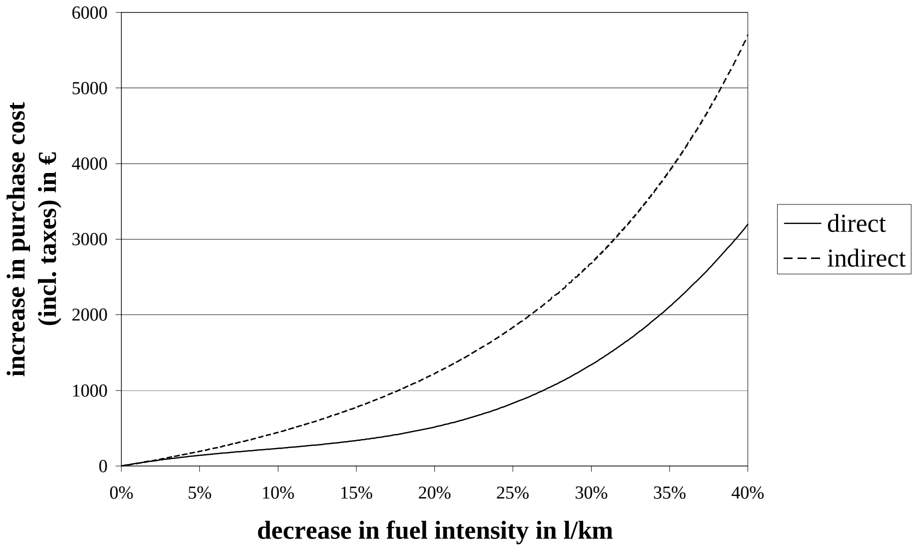


Figure 4.4. Cost of fuel efficiency for small gasoline cars (<1,4 l)

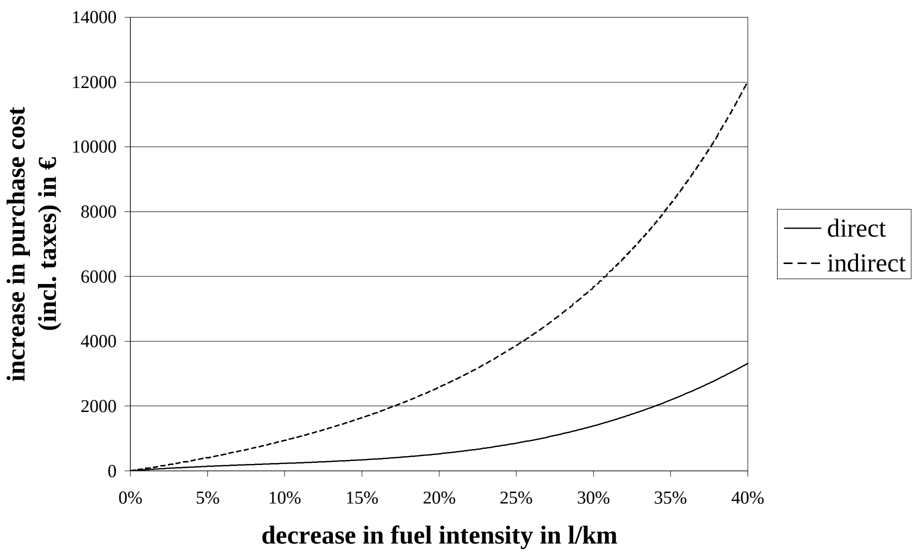


Figure 4.5. Cost of fuel efficiency for medium gasoline cars (1,4–2,0 l)

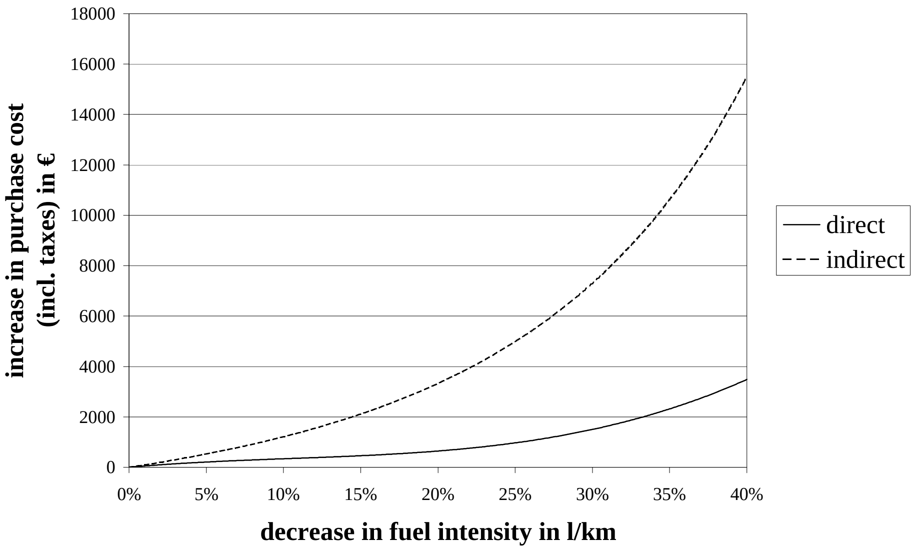


Figure 4.6. Cost of fuel efficiency for big gasoline cars (>2,0 l)

these technologies become available. We will call this evolution the *autonomous progress* and discuss it in the next section.[8]

This difference in approach may also explain why the formulae by P. ten Brink et al. (2005) result in a smaller cost increase for gasoline compared to diesel cars for an identical decrease in fuel intensity, an observation which is not in line with formula (4.2).

A smaller issue that may also imply a difference between both approaches is that P. ten Brink et al. (2005) included measures that affect real world fuel intensity rather than test cycle behaviour. The European Conference of Ministers of Transport [ECMT] and International Energy Agency [IEA] (2005) discusses such fuel efficiency improvements that are not reflected in test cycle figures and may result in a net user cost reduction. Imperfect information is identified as the reason for non-implementation of these technologies. As such measures fall beyond the scope of our study, we will not further discuss them here.

Technology curves which include negative cost figures are not a useful approach of a welfare analysis where the reference point should be the user cost optimised technology at each point in time in order to correctly identify the impact of policy scenarios. In our assessment of different fuel efficiency

[8]Blok, Jager, Hendriks, Kouvaritakis, and Mantzos (2001) do a similar comparison of CO_2 abatement costs in the bottom-up GENESIS model and the top-down PRIMES model. They find negative cost figures in GENESIS in the range between the 2010 frozen technology level and the baseline level. For the PRIMES model they point out that such negative cost options are already incorporated in the baseline.

policies (sections 4.3 and 4.4) we therefore decided to apply the indirect approach combined with an autonomous progress assumption (see next section). This approach also provides a clear link between fuel price and fuel efficiency. We will discuss the implementation of our simulation tool in section 4.2.4.

4.2.2. Autonomous progress

In the previous section we studied the evolution of fuel efficiency resulting from an increase in fuel prices. Here we look at what happens to fuel efficiency over time if fuel prices do not change (in real terms).[9]

There seems to be some evidence that a constant improvement of fuel efficiency should happen as a result of *research and development* efforts as well as of *learning-by-doing* (IEA, 2000). This is confirmed by Verbeiren et al. (2003) who expect an annual improvement of 0,6% for the conventional technologies. Small and Van Dender (2006) identify an annual improvement of even 2,0% for the fuel intensity of the US vehicle stock over the period 1980–2001 which cannot be explained by the evolution in fuel costs, mandatory efficiency standards (CAFE), income or urbanisation.

At the other hand, R. M. M. Van den Brink and Van Wee (2001) observe no decrease in fuel intensity for the average new private car in the Netherlands in the 1985–1997 period. The authors study the evolution of the technological properties over this period and find that the observed technological improvements were cancelled out by mainly an increase in vehicle mass of the average car resulting in a constant fuel intensity. This confirms the existence of technological progress but does not directly allow to draw the conclusion that it should result in more fuel efficient cars.

If we study the results by R. M. M. Van den Brink and Van Wee (2001) more closely, we observe that part of the weight increase is the result of a shift towards larger engine sizes. The authors indicate that without this shift over the period 1985–1997 the average new private car (in 1997) would have been 6% more fuel efficient. Correcting for this evolution results in a decrease by 4,1% for the fuel intensity of a gasoline car with a constant engine size over the 1985–1997 period. We also observe gasoline fuel prices in 1997 to be lower than in 1985 (constant prices), which should have resulted in an increase of about 3% of the fuel intensity (based on formula (4.4)) if there was no autonomous progress. Assuming that the difference between both evolutions is the autonomous progress, we find an average annual decrease of the fuel intensity of about 0,6% for a constant engine size gasoline technology.

The past research referred to in this section does not provide evidence on differences in autonomous progress between engine size classes or fuels.

[9] Throughout this chapter we express all costs in constant prices (i.e. compensated for inflation). The monetary unit used is the value of the euro in 2000.

4.2.3. Test cycle is not real world

There seems to be some evidence that fuel efficiency differs significantly between test cycle and average real world driving behaviour.

R. M. M. Van den Brink and Van Wee (2001) provide a comparison between real world fuel consumption and test cycle measurements. The real world consumption for the average new 1997 gasoline car is reported to be 10% higher than Eurotest (93/116/EC) figures. For Germany, the difference would amount to 17%. The authors expect the difference to increase due to the introduction of direct injection gasoline cars and the increasing share of airco-equipped cars in new sales.

ECMT and IEA (2005) provide a literature review on the difference between test cycle and real world consumption. However they do not provide evidence that the gap should increase as a result of new technologies. As for the existing gap they draw the conclusion that for Europe not much is known because only a few studies are available.

4.2.4. TREMOVE Belgium

In this section we discuss how we implement the link between fuel price, fuel intensity and resource costs in the TREMOVE modelling framework. This allows to assess the environmental impact and welfare cost of the implementation of fuel efficiency policy measures.

The Model

We use the TREMOVE model for Belgium. An overview of the model specification is provided in appendix C, in our application here we include the extensions that are discussed in chapter 3 (e.g. technology choice model for private cars). The model implemented in this chapter limits the availability of car technologies to the conventional ones (see table 4.1): three engine size classes for diesel and three classes for gasoline technologies (as opposed to chapter 3 where the availability of a range of alternative technologies was considered). The share of LPG technologies is fixed to 1% of the sales of gasoline technologies.

We here explicitly assume that the technology categories presented in table 4.1 cover all private car sales. As indicated by NRC (2002) failing to properly define the distinction between private cars and trucks led to aspects of USA fuel efficiency standards (CAFE program) not having functioned as intended.

We implement the indirect approach presented in section 4.2.1 as it allows for a consistent welfare assessment. This link between fuel prices, fuel intensity and resource costs is assumed to apply to all road technologies (not only private cars).[10]

[10]In the simulations in sections 4.3 and 4.4 we will mainly focus on private cars. For other

The straightforward implementation of the indirect approach includes an implicit assumption of reversibility: if fuel prices first go up and then go back down to the original level, the fuel intensity will finally come back to the original level (apart from any autonomous progress over time). There is some evidence that this reversibility does not hold and that a hysteresis effect plays (Dargay, 1997; Gately, 1992; Walker and Wirl, 1993). In contrast Small and Van Dender (2006) assume the link between fuel prices and fuel to be symmetric. As the focus of our study here will be limited to decreases in fuel intensity, we decided not to implement asymmetry in order to keep the model simple.[11]

The existing emissions module includes an assumption on the difference between test cycle and real world fuel efficiency. At the EU level a difference of 15% was assumed (constant over time). The emissions module we use here is based on the TREMOVE 2 model. We refer to the documentation of the TREMOVE 2 model (G. De Ceuster et al., 2005), for a full discussion of its implementation. The exact implementation does not matter much for our simulations here, as we will explicitly focus on improvement of test cycle fuel efficiency. Any fixed supplement (be it 5% or 15%) will only be reflected in total emissions figures (and corresponding external costs).

The Baseline

A baseline scenario is constructed for the period 1995–2020. This *business-as-usual* scenario simulates what happens in a situation where no new policy measures are implemented apart from those already decided. The aim of the baseline is to function as a *reference* for the fuel efficiency policy simulations (see sections 4.3 and 4.4), to allow for a consistent assessment of the impact of the policy measure on technology shift, modal shift, emissions reduction and welfare cost.

One should however not consider the baseline scenario as a projection or forecast, TREMOVE not being a forecast model. The TREMOVE model is a simulation tool providing a consistent framework for the assessment of what would happen if the exogenous variables follow a given evolution.

This section discusses the baseline evolution for fuel prices/taxes and fuel efficiency of private cars. For a more comprehensive discussion of the baseline scenario (including fuel prices, taxes and efficiency of other modes) we refer to the model specification in appendix C.

modes there will be only small changes in fuel intensity resulting from the baseline evolution of fuel prices.

[11] In the baseline scenario an occasional decrease in fuel price may result in a small increase in fuel intensity. However, these effects are of a smaller order of magnitude compared to the simulations in sections 4.3 and 4.4.

Fuel cost Fuel cost per litre consists of ex-tax costs and taxes. The ex-tax costs for the historical period (1995–2002) are based on statistics by IEA (2003). The evolution beyond 2002 is based on PRIMES-transport forecasts (Knockaert et al., 2002) on evolution of crude oil and refining costs, assuming a constant margin for fuel distribution.

The introduction of sulphur free (10 ppm) fuels in 2009 is assumed to raise the ex-tax cost by 3% for gasoline and 5% for diesel.

The baseline ex-tax fuel price evolution is illustrated by figure 4.7.

Taxes are based on IEA (2003) for the historical period and kept constant at the level of 2003, apart from the Cliquet system (Federale Overheidsdienst, Kanselarij van de Eerste Minister, 2003) that has been implemented to determine excise rises for the period 2004–2008 (diesel and gasoline).

Fuel Efficiency As part of the EU strategy on specific CO_2 emissions from new private cars a data collection system was implemented (European Parliament and Council of the European Union, 2000). From this database we obtain CO_2 emission figures for the different vehicle classes (engine size and fuel) for the year 2000. To convert these emission figures to volumetric fuel consumption we applied the methodology of the TREMOVE emissions module.

The historic evolution 1995–2000 has been based on the monitoring reports by the EU commission. These reports provide evolution of average CO_2 emissions for new vehicles by fuel (but not by engine size). We applied this

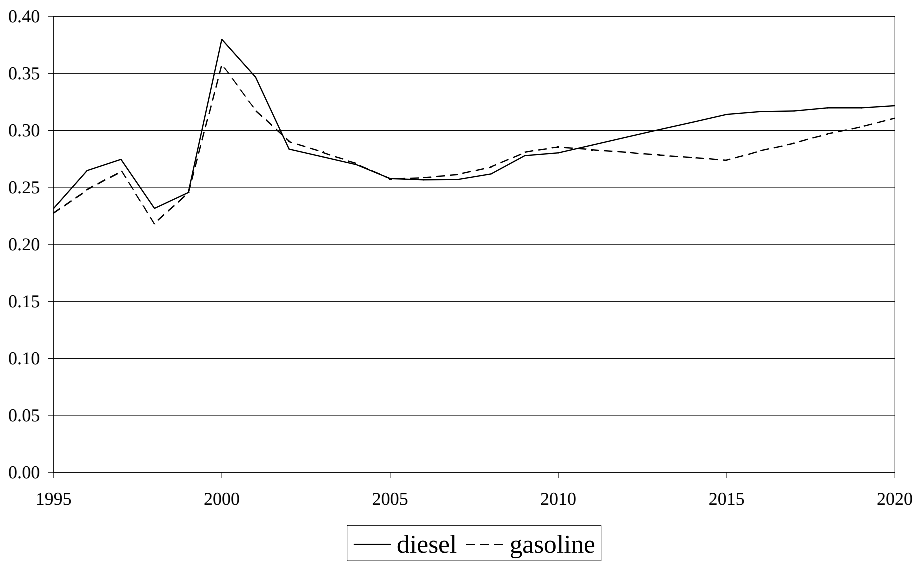


Figure 4.7. Baseline evolution of ex-tax fuel cost for private cars (in €/l)

evolution to the 2000 figures.

For the application of formula (4.4) we need a reference fuel price p_0 and fuel intensity f_0 for each year in the modelling period (2000–2020). For the fuel price we take the year 2000 value as reference for the 2000–2020 period, whereas for the fuel intensity we start from the year 2000 values and assume an annual autonomous progress of 0,6% (see section 4.2.2).[12] Together with the baseline fuel price evolution (see above) this allows us to apply formula (4.4) to calculate the baseline fuel intensity (see figure 4.8) and formula (4.5) for the corresponding baseline resource cost.

Emissions Emissions (and fuel consumption) of road transport activity are calculated making use of the emissions module of TREMOVE 2 which is based on COPERT III methodology. For an extensive discussion of the emissions module we refer to the respective model documentation (G. De Ceuster et al., 2005; Ntziachristos and Samaras, 2000).

The baseline evolution of the most important pollutants is presented in figure 4.9. We remind the reader that the baseline simulates a situation where no additional policy measures are implemented (apart from those already

[12]Our rate of autonomous progress is based on the literature reviewed in section 4.2.2. An alternative approach would be to use the direct cost curves presented by P. ten Brink et al. (2005) and select the technologies with a negative fuel efficiency cost to provide a measure for autonomous progress.

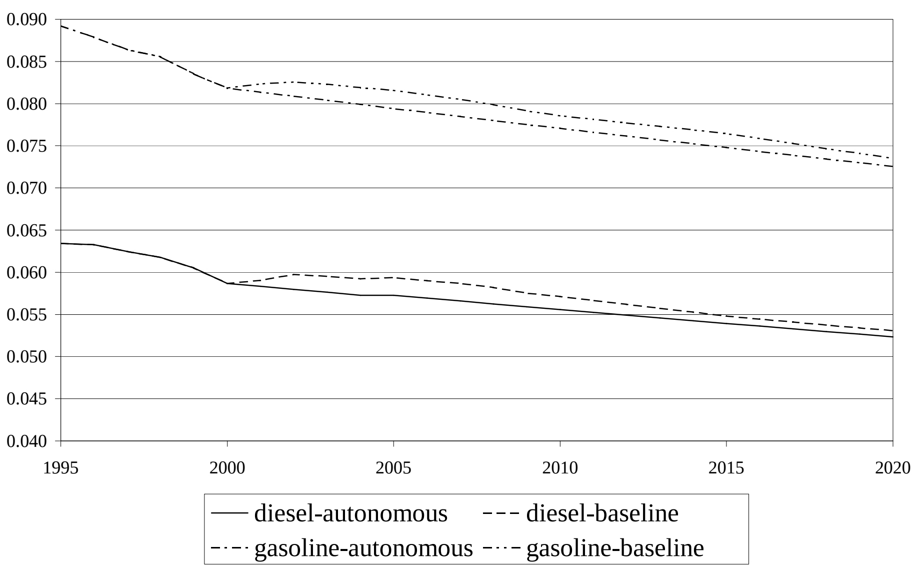


Figure 4.8. Baseline evolution of fuel intensity of new private cars with medium engine size (in l/km)

decided). This implies that no further improvements of emission technologies are considered beyond Euro 4 (for private cars) or Euro 5 (for heavy duty vehicles). This explains the status quo in overall transport emissions level from 2015 on in the baseline. To assess external costs from transport emissions we apply marginal external emission cost coefficients for all pollutants.[13]

Emissions of CO_2 by road modes are linked to fuel consumption based on the carbon content of the fuel. The marginal external cost coefficient for CO_2 emissions reflects a reference value for economy wide abatement cost (see figure 4.10). The rationale for using abatement cost (rather than environmental impact) is that total EU-wide CO_2 emissions are capped by the Kyoto agreements. An increase of CO_2 emissions in one sector needs hence to be compensated by a decrease elsewhere in the economy. The value we use for external abatement cost is provided by TREMOVE 2 and is based on Holland, Hunt, et al. (2005). This value is of a similar order of magnitude of values provided in literature for marginal environmental impact by CO_2 emissions.

[13]Marginal external emission cost coefficients are based on TREMOVE 2 values. An overview is presented in appendix C, we refer to the model documentation (G. De Ceuster et al., 2005) for a full discussion of the issue.

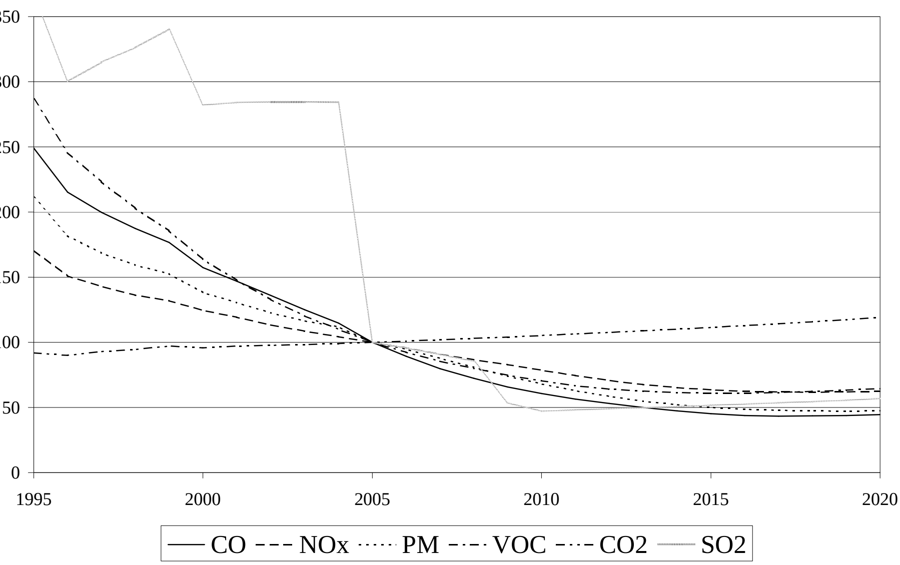


Figure 4.9. Baseline evolution of overall transport emissions (index: 2005 level = 100)

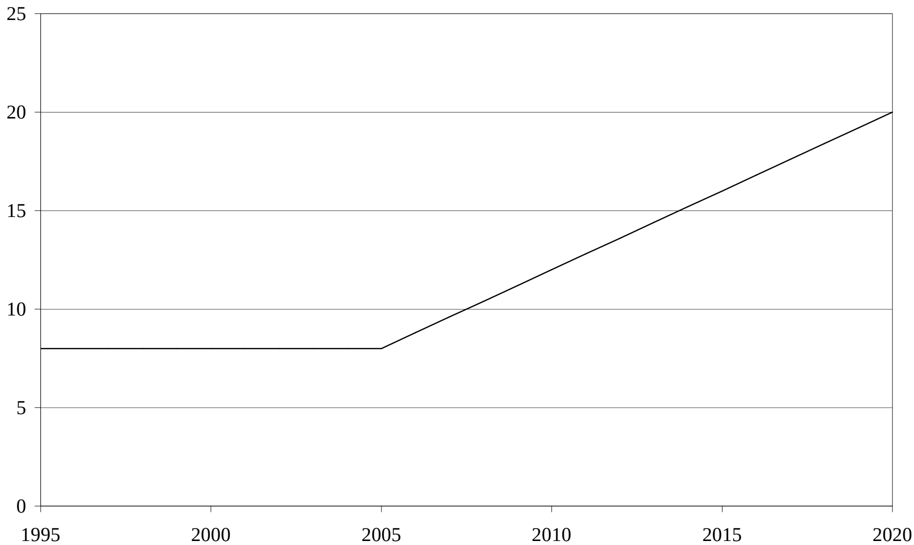


Figure 4.10. Evolution of marginal external cost coefficient C_p of CO_2 emissions (in €/t)

4.3. EU-policy: the agreements

Three agreements have been made between the European Commission and the car manufacturers. These commitments have been concluded with the European (ACEA), the Japanese (JAMA) and Korean (KAMA) automobile industries. The manufacturers mainly commit to improve fuel efficiency by technological improvements to reach an average level of specific CO_2 emissions from new private cars of 140 g/km by 2008.[14] In this section we study the welfare and environmental impact for Belgium of an implementation of this policy approach.

4.3.1. Literature

Whereas the set target of 140 g/km seems to be straightforward, the agreements are not clear on how it is to be reached. An important issue that has been raised in past research is that of the share of diesel vehicles by 2008: a shift towards diesel basically reduces specific CO_2 emissions. In the reports monitoring the evolution of CO_2 emissions of new cars,[15] the average CO_2 emission factor is used to evaluate the progress made by the manufacturers.

[14] To be correct, the target year is 2008 for ACEA and 2009 for JAMA and KAMA. In this study, we will assume one target year of 2008 for simplicity.

[15] A yearly report is issued as a result of the monitoring decision (see above), we will refer to these reports further on in the text as the *CO_2 monitoring reports*.

The observed reduction is clearly partially a result of a shift from gasoline to diesel cars. It is not clear in how far this can be considered as being a technological improvement: the agreements indicate that the reductions to meet the 140 g/km target have to be realised by technical measures taken by the manufacturers.[16]

Earlier research by COWI A/S (2002) assumed the reduction target to be realised for both fuels separately. That would mean a 25% reduction of fuel intensity between 1995 and 2008. Above this improvement, a 2–3% CO_2 reduction is assumed as resulting from the introduction of 10 ppm sulphur fuels.[17] Finally, a rebound effect[18] is expected by COWI, requiring an additional reduction of 1,7–2,9%. The overall reduction in fuel intensity necessary in the 1995–2008 period is estimated to amount to 28,7% for diesel cars and 30,9% for gasoline cars. Plotkin (2001) follows a similar interpretation in fixing the reduction target at 25% assuming no change in fuel mix.

P. ten Brink et al. (2005) assume that the market split diesel-gasoline evolves to reach equal shares by 2008 on the basis of market insights and expert judgement. In this setting they simulate the least cost option (based on direct cost curves) to reach the 140 g/km measure for different implementations of corporate average fuel economy standards.

4.3.2. TREMOVE

To avoid problems of inconsistencies as well as the uncertainties linked to expert judgement on the optimal diesel-gasoline share under the policy scenario in consideration, we here use the TREMOVE modelling framework for Belgium with the implementation of the indirect approach in order to simulate a least cost realisation of the 140 g/km approach and to provide insight in the environmental impact and welfare cost of this policy measure for the 2000–2008 period.[19]

[16] The 2003 report by the Commission (Commission of the European Communities, 2004) states on this issue: *In addition, as requested by Article 10 of Decision 1753/2000, the Communications for the intermediate target year (monitoring year 2003 for ACEA and JAMA, and 2004 for KAMA) will address questions related to the reasons for the observed reductions. It has to be thoroughly assessed whether reductions registered are due to technical measures by the manufacturers, or due to changes in consumer behaviour.*

[17] COWI A/S (2002) expects that the reduction of fuel sulphur content induces a reduction of CO_2 emissions due to lower carbon content and new technology.

[18] It is expected that improved fuel economy incites consumers to buy bigger cars, which in turn increases average CO_2 emissions.

[19] We here implicitly assume the year 2000 as the starting point for the agreements. The publication of the agreements in the Official Journal is in 1999 and 2000. As the TREMOVE model uses year 2000 data as base for private car user cost, it seems appropriate to use 2000 as starting point. Note however that the formal agreement between the association of European car manufacturers (ACEA) and the EU Commission dates from somewhere in 1998.

Implementation

One issue that arises in applying the TREMOVE model for Belgium is that it is not specified how the effort to reach the EU targets is to be distributed over the countries. As the existing levels of fuel intensity differ over the countries it is probable that the target will not be reached in all countries (only the EU average target is set).

Our study is focusing on the Belgian market only. As the 2000 specific emission figures on this market are close to the EU average, we assume for our assessment that the 140 g/km is to be met for the Belgian car market.

We assume that the car manufacturers will change fuel efficiency such that the 140 g/km target is met at the least cost for the consumer.[20] Referring to formula (4.1) and with e_i the per kilometre CO_2 emissions of technology i this means that $\frac{dUC_i}{de_i}$ has to be equal over all technologies i:

$$\forall i : \frac{dUC_i}{de_i} = \left[\frac{dRC_i(f_i)}{df_i} + p\right]\frac{df_i}{de_i} = \left[\frac{dRC_i(f_i)}{df_i} + p\right] v_i = -C \tag{4.6}$$

with v_i the CO_2 emissions per fuel unit (for the fuel consumed by technology i) and C a constant.

From equation (4.5) we obtain $\frac{dRC_i}{df_i}$ as a function of f_i:

$$\frac{dRC_i}{df_i} = -p_{i,0}\left(\frac{f_i}{f_{i,0}}\right)^{\frac{1}{\epsilon}} \tag{4.7}$$

By substituting $\frac{dRC_i}{df_i}$ in equation (4.6) by expression (4.7) and reworking somewhat we obtain:

$$\forall i : f_i = f_{i,0}\left(\frac{p_i + v_i \cdot C}{p_{i,0}}\right)^{\epsilon} \tag{4.8}$$

This formula expresses how the efficiency standard in 2008 should be implemented such that it results in the lowest average cost for the users.

For the period beyond 2008 we assume a fuel efficiency standard that becomes more stringent at the pace of the autonomous technological progress.

In a final step the period 2000–2008 has to be filled in. We decided to use figures from the monitoring database for 2001 and 2002. Beyond 2002 we linearly interpolated with the optimal 2008 fuel intensity figures, assuming an identical (absolute) effort to improve fuel efficiency for all intermediate years.

[20] Least cost for the users here means lowest average user cost disregarding consumer reactions in terms of car use. The specification of the TREMOVE modelling framework includes a fixed annual mileage assumption. Such a least cost scenario could be achieved using tradable specific emission rights between car manufacturers.

As for the introduction of low sulphur fuels we assume that this does not have a direct impact on fuel efficiency (but rather facilitates new technologies to be introduced after 2009).[21]

The specification of the TREMOVE modelling framework includes a fixed annual mileage per vehicle. A change in generalised user cost leads to a change in vehicle activity demand and a proportional change in the vehicle stock size. Consumer reactions in terms of annual mileage per car are not modelled. The literature describes a rebound effect where lower fuel costs induce an increase in mileage per vehicle. This effect is not included in our modelling, we will briefly discuss its potential impact in section 4.5.

Results

The fuel efficiency evolution is presented in figure 4.11. The baseline fuel intensity is somewhat above the autonomous technological progress as a result of an observed decrease in fuel prices after 2000. The difference becomes smaller towards 2020 in line with increasing fuel prices (see figure 4.7 for the baseline evolution of ex-tax fuel prices). The effect of the fuel efficiency standard in the policy simulation scenario is obvious.

[21]COWI A/S (2002) expects that the reduction in sulphur content induces a 2–3% reduction of specific CO_2 emissions due to lower carbon content and new technologies.

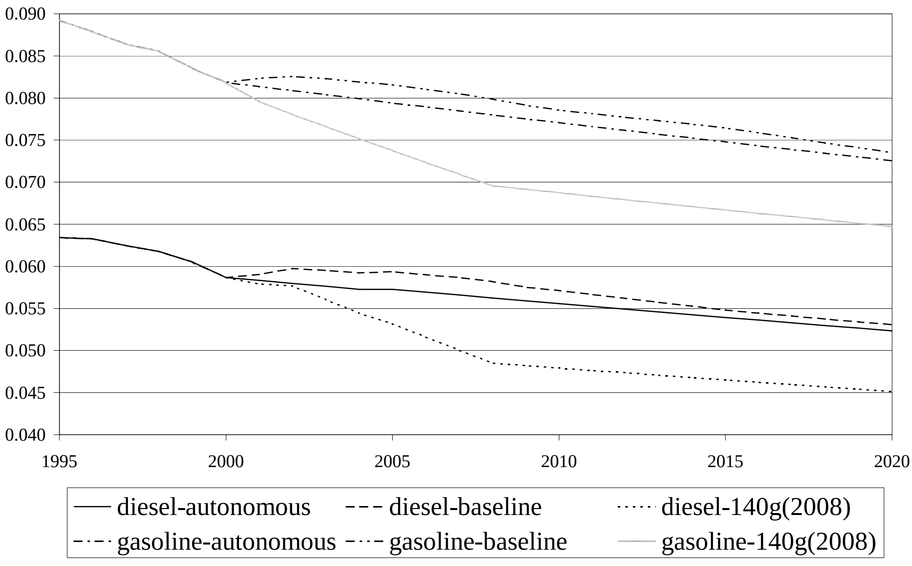


Figure 4.11. Impact of EU policy on fuel intensity of new private cars with medium engine size (in l/km)

The resulting least-cost (for the users) reduction of specific CO_2 emissions to 140 g/km is realised by reducing fuel intensity for diesel technologies by 16,7% (same for all engine sizes) compared to baseline levels, whereas for gasoline cars a smaller improvement of 12,9% is optimal.

The optimal burden sharing resulting in a larger (relative) contribution by diesel technologies could be expected from expression (4.2), considered that the volumetric price (including taxes) of diesel fuel is lower than gasoline in Belgium.

The impact of the fuel intensity decrease on the technology lifetime user cost is illustrated by figure 4.12. We observe a limited impact on simulated user cost in 2008 in the order of 1% to 1,5% depending on fuel and engine size.

The increased user cost is reflected in small changes in the vehicle stock composition, as presented in figure 4.13. We see a small shift from medium and big to small cars.

The change in lifetime user cost of private car technologies results in an increase of the generalised prices of private car transport of about 0,2% in urban areas and slightly over 0,4% in non-urban areas (see figures 4.14 and 4.15). The relative increase in generalised prices (figures 4.14 and 4.15) is smaller than the corresponding increase in new private car user cost (figure 4.12). This difference can be explained by conceptual differences between the generalised transport cost and the vehicle lifetime user cost: the former

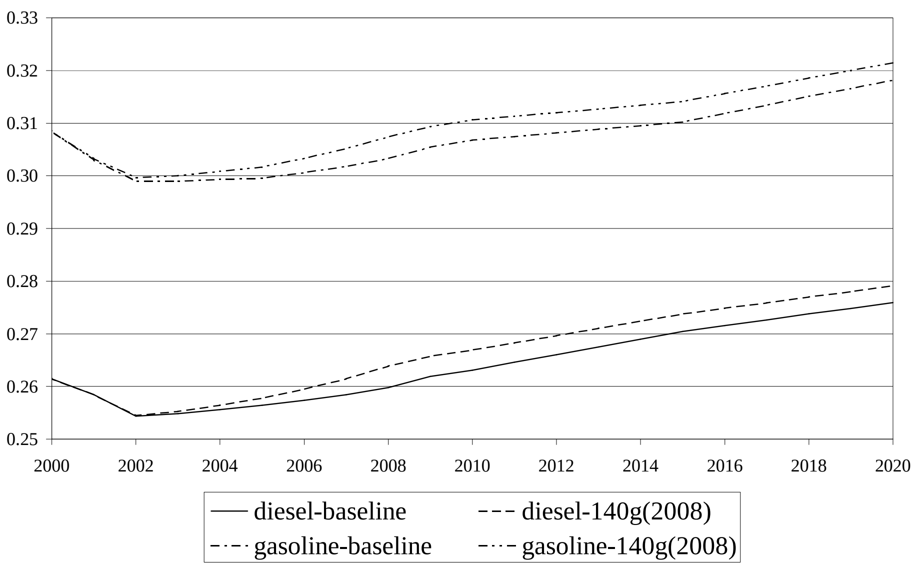


Figure 4.12. Impact of EU policy on lifetime user cost of new private cars with medium engine size (in €/km)

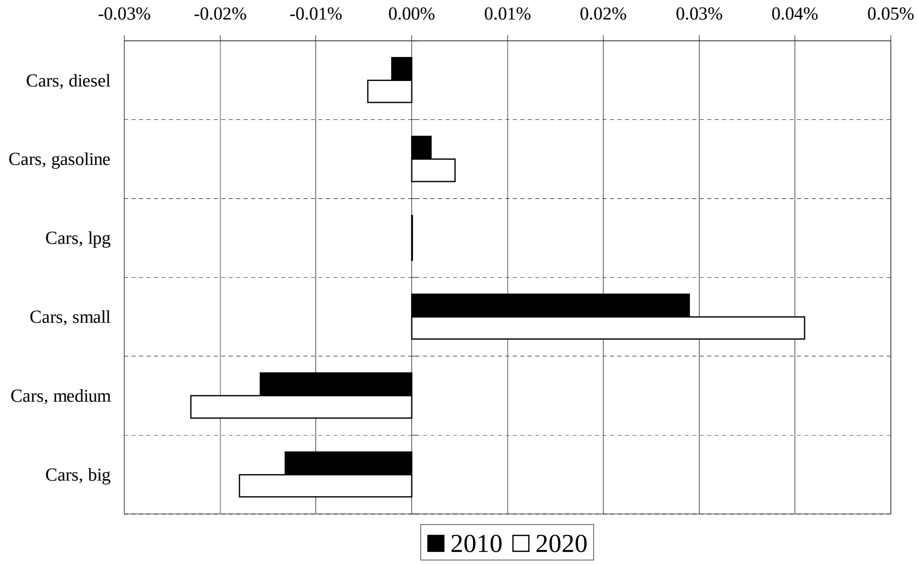


Figure 4.13. Impact of EU policy on private car stock composition (change of technology share in percentage point compared to base case levels)

includes time costs which the latter does not, and the former reflects the user costs of the average car (in the vehicle stock) whereas the latter only reflects cost levels of new cars. For the other modes we observe a status quo or small reductions in generalised prices: higher prices for private car result in lower traffic levels, a corresponding increase in average speed and hence a reduction in the time costs for the other modes.

The reduced time costs for the other modes together with the increase in generalised prices for private cars result in a modal shift (figures 4.16 and 4.17). Part of this shift is towards public transport, resulting in an increase in frequencies and the corresponding decrease in waiting time further contributes to the decrease in time costs for these modes. The shifts increase over time, reflecting the increasing share of more expensive technologies in the private car stock as a result of the fuel efficiency standard. The decrease in total passenger transport demand aggregated over all modes amounts to 0,3% by 2020.

The impact of the fuel efficiency standard on activity demand does take into account the effects of changes in income level resulting from the measure (through changes in tax income for the government). However, the physical distribution of activities as well as the supply of road infrastructure are kept constant. We will come back to the limitations of the TREMOVE model in section 4.5.

The changes in modal demand and private car stock composition result

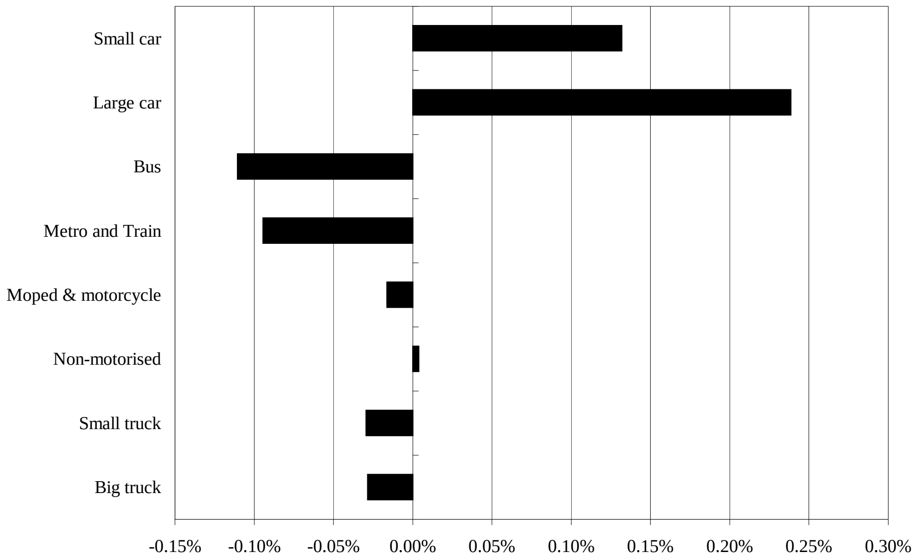


Figure 4.14. Impact of EU policy on modal generalised prices in urban regions (in % change compared to base case levels)

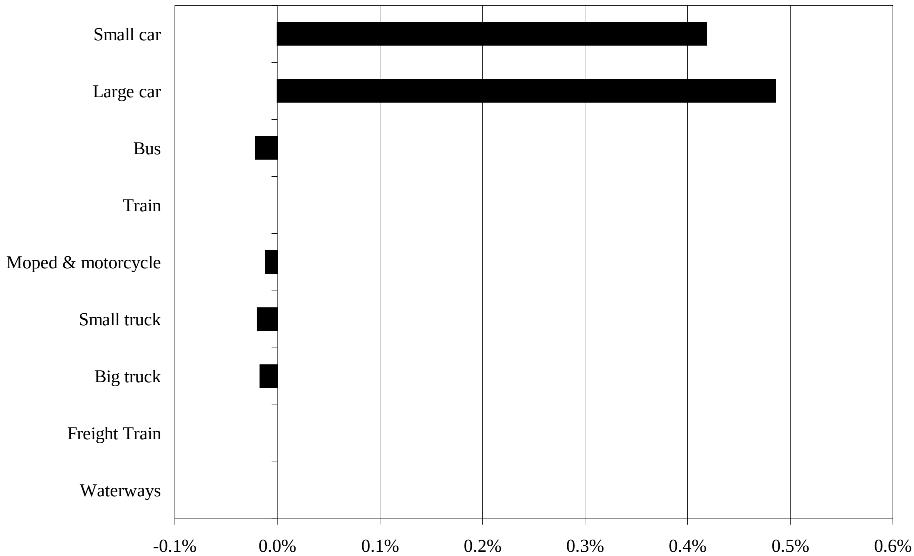


Figure 4.15. Impact of EU policy on modal generalised prices in non-urban regions (in % change compared to base case levels)

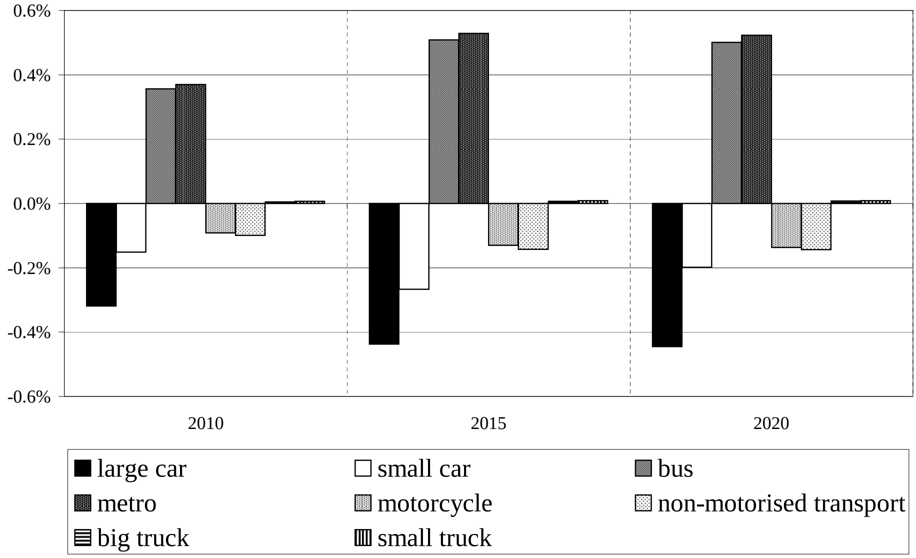


Figure 4.16. Impact of EU policy on Brussels passenger transport activity (in % change compared to base case levels)

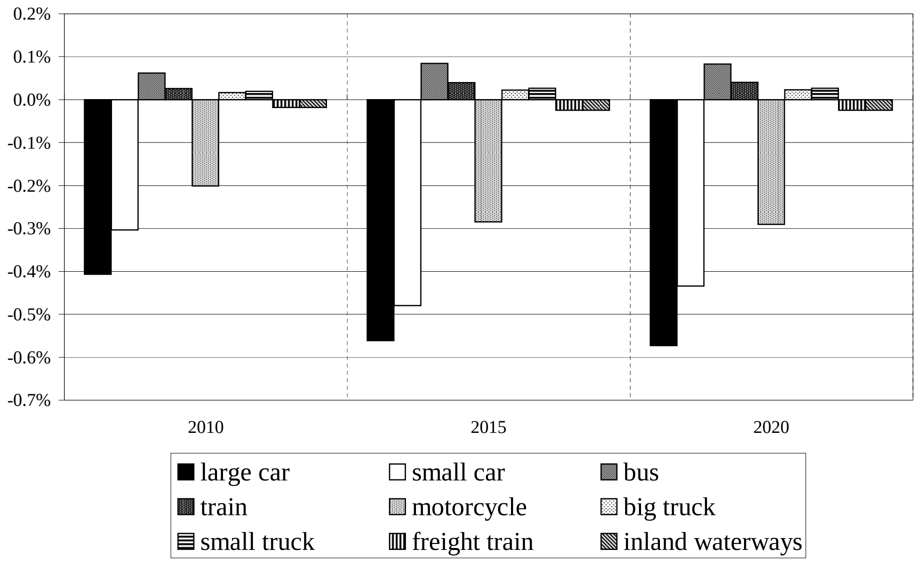


Figure 4.17. Impact of EU policy on non-urban passenger transport activity (in % change compared to base case levels)

in a change in emissions presented in figure 4.18. The overall transport activity CO_2 emissions decrease by 7%. For other pollutants we observe small decreases. The decrease in SO_2 emissions is somewhat larger.

The social cost of the efficiency standard is presented in figure 4.19. As discussed above the increase in user cost of private car technologies results in an overall loss of consumer surplus in passenger transport activity. For freight transport there is a small gain resulting from reduced congestion. We also observe a net cost for the government which corresponds to a loss in tax income. The MCPF term (marginal cost of public funds) represents the efficiency gain of lowering labour taxes through a shift of taxes (via higher transport taxes) to non-labour income taxes.[22] The loss in consumer surplus and decrease in tax income is much larger than the overall reduction in external emission cost, hence the net welfare effect is a cost. This is reflected in the 2005 net present value of the efficiency standard which amounts to 3651 million euro (3782 if excluding the change in external emission cost).

Studying the change in consumer surplus for passenger transport activity (see figure 4.20), we observe a shift from fuel cost to non-fuel cost. It is interesting here to note that the share of taxes in both user cost components is not equal: fuels are more heavily taxed than other costs. As a result, the shift away from fuel expenses results in a decrease in tax income for the

[22] We assume that there are also other sources of income that are taxed but that only taxes on labour income are reduced. The value of the MCPF coefficient used in our simulations is 6,6%.

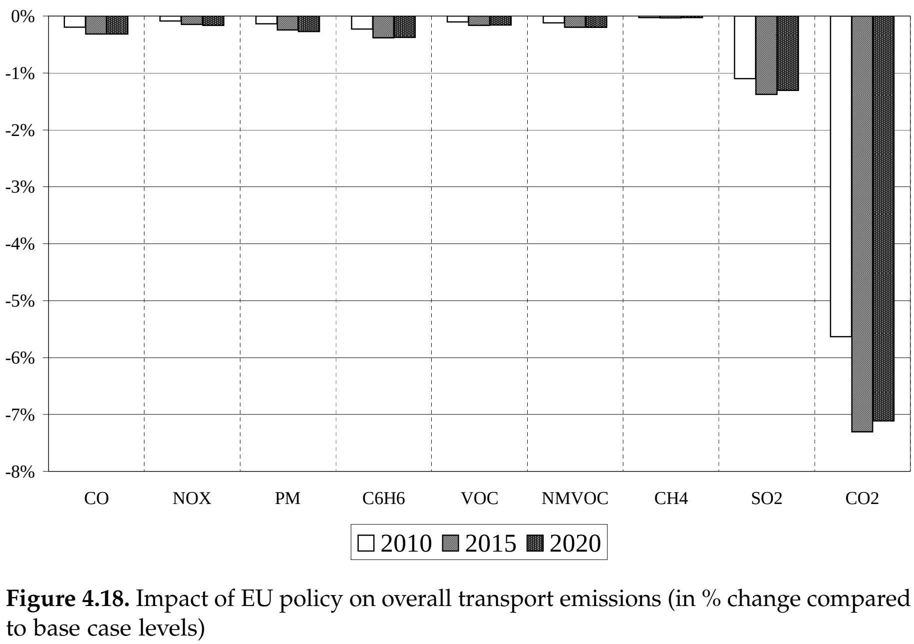


Figure 4.18. Impact of EU policy on overall transport emissions (in % change compared to base case levels)

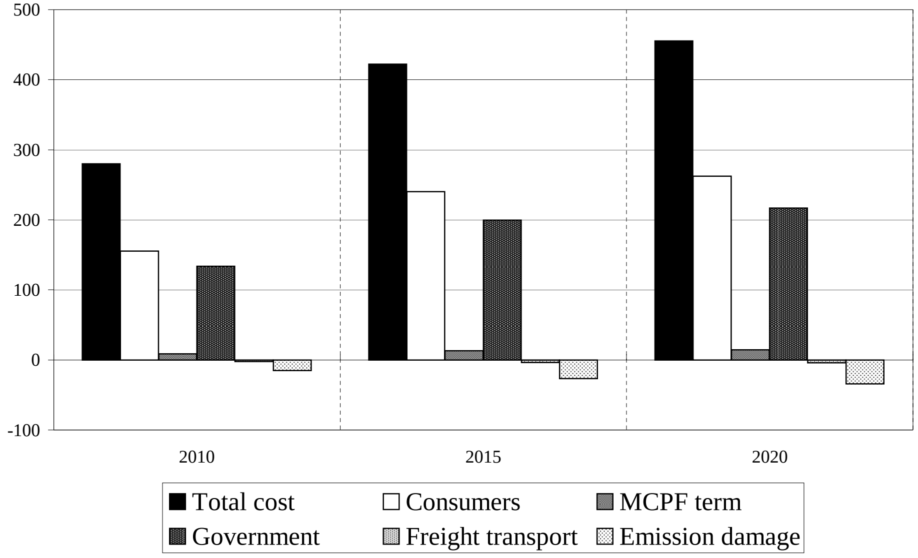


Figure 4.19. Annual welfare cost of EU policy (in million €2000 compared to base case)

government as we already noted. The improved fuel efficiency forces the user to substitute taxes for resource costs, resulting in the cost for society being much higher than the cost to the user.

The simulation indicates that the fuel efficiency standard is effective (it reduces CO_2 emissions) but comes at too high a cost: the cost to society is many times the reduction in external emission cost. The reduction of CO_2 emissions comes at a cost of 270 €/t in 2010. The high cost of CO_2 reductions in the private car transport sector indicates that it may be more advisable to reduce CO_2 emissions in other sectors where abatement costs are lower.

This finding is in line with Stern (2007) who presents marginal abatement costs for the UK in 2020 for selected technologies. Private car fuel efficiency comes in as by far the most expensive technological approach at about 275 euro per ton of CO_2.

4.4. Beyond 2008: standard or tax?

As the 2008/9 horizon of the CO_2 emission policy for private cars approaches, the EU Commission prepared for a next round of fuel efficiency improvements, setting out an ambitious target of 120 g/km for new private cars to be met by 2012.

P. ten Brink et al. (2005) made an assessment of the further reduction towards 120 g/km and studied how this could be realised at the smallest cost for society. They compare different settings based on how the target

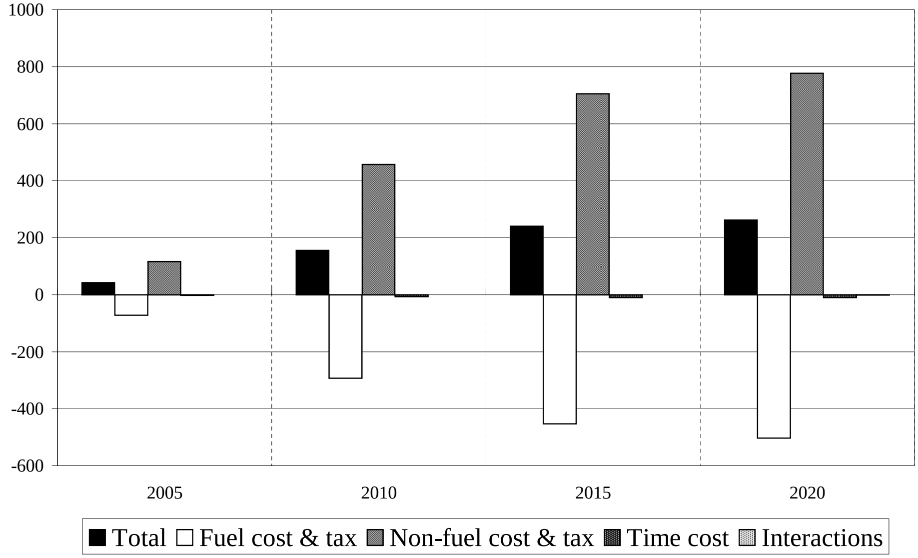


Figure 4.20. Decomposition of change in consumer surplus in passenger transport activity (in million €2000 compared to base case)

is formulated: on a per car basis, per manufacturer or per association of manufacturers (as is the existing tax). They further study different scenarios on how the burden should be shared between fuel and size classes. Their study however does not include an assessment of modal demand evolution.

In this section we will simulate an efficiency standard for the 2008–2012 period in the same way as we did for the pre-2008 era. In a next step we will compare it to a CO_2 emission tax. Such a tax guarantees that a given external emission cost reduction is realised at the lowest cost for society as it levels the abatement costs over the different transport markets (Kolstad, 2000).

4.4.1. Implementation

The further reduction of the CO_2 emissions by a subsequent efficiency standard is simulated much in the same way as for the 2008 standard. We refer to section 4.3.2 for the details.

In a next step we simulate a CO_2 emission tax for private cars as an alternative measure to reduce CO_2 emissions. This is implemented by replacing existing fuel taxes on gasoline and diesel (for private cars) by a tax that is proportional to the carbon-content of the fuel in the post-2008 period.

4.4.2. Results

Efficiency standard

The least user cost implementation of the 120 gram CO_2 per kilometre efficiency standard is by reducing by 2012 the fuel intensity by 27,0% for diesel and 22,8% for gasoline technologies compared to the baseline level, or a further improvement of 13,4% (diesel) or 11,7% (gasoline) compared to the 140 g/km fuel efficiency standard. This evolution is presented in figure 4.21 for medium engine size technologies.

The increase in per kilometre user cost is presented in figure 4.22. The impact in 2012 is in the order of magnitude of 4–5,5%, which is larger than for the original 140 g/km standard.

The relative changes in user cost do not induce major technological shifts (see figure 4.23).

The modal generalised prices follow an evolution which is qualitatively much the same as for the 140 g/km standard, be it that the order of magnitude is somewhat larger now reflecting the larger user cost increase of the private car technologies.

Changes in generalised prices result in demand changes. Overall demand for passenger traffic decreases by 0,7% in 2020 (compared to 140 g/km standard), whereas freight activity remains stable. Changes in modal demand (and hence modal shift) follow a pattern which is qualitatively similar to what

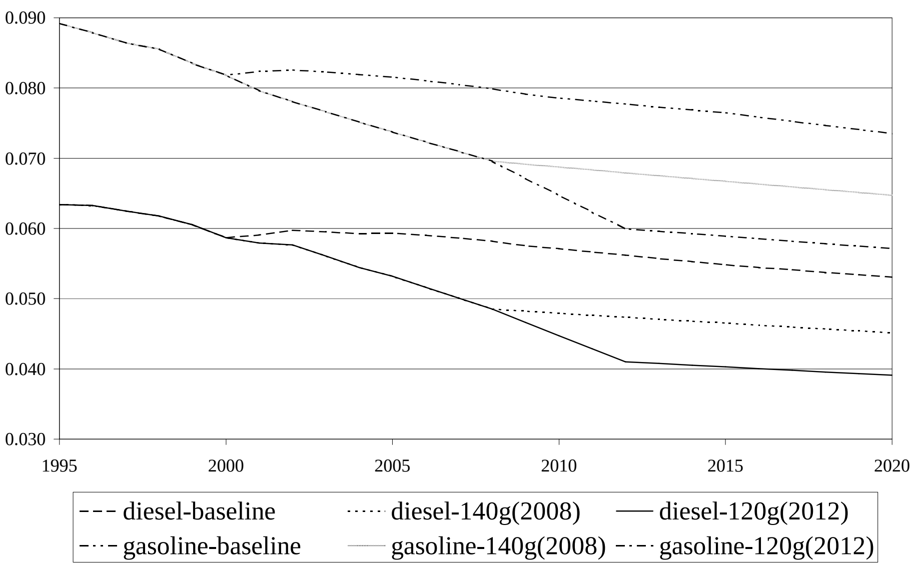


Figure 4.21. Impact of enhanced fuel efficiency standard on fuel intensity of new private cars with medium engine size (in l/km)

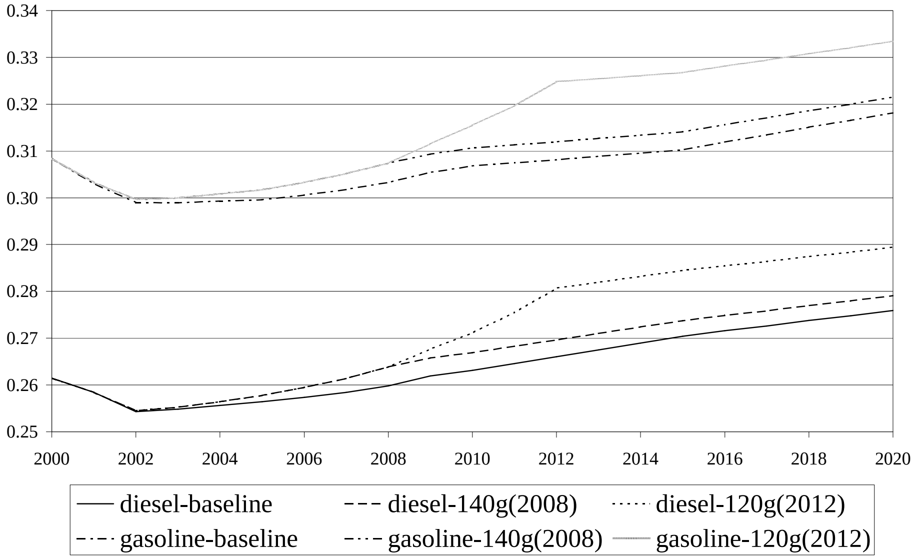


Figure 4.22. Impact of enhanced fuel efficiency standard on lifetime user cost of new private cars with medium engine size (in €/km)

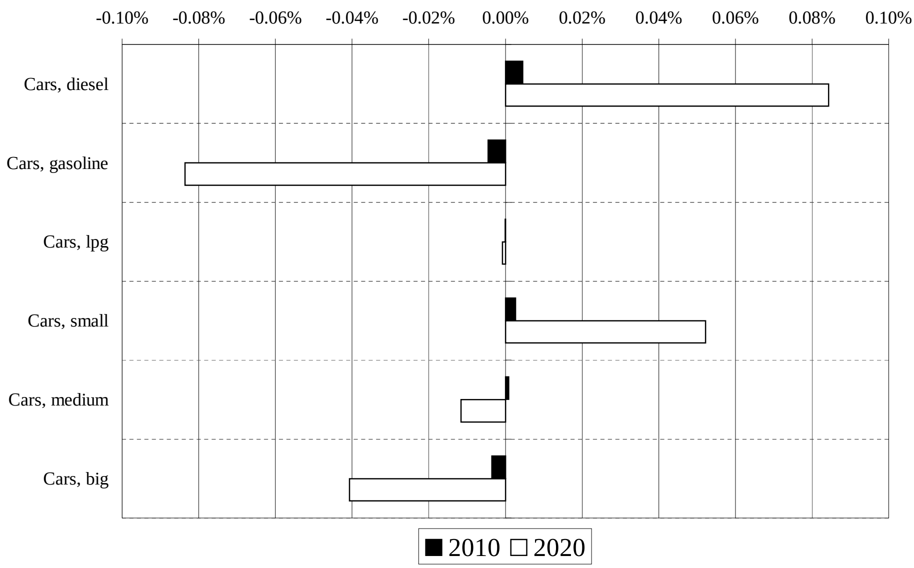


Figure 4.23. Impact of enhanced fuel efficiency standard on private car stock composition (change of technology share in percentage point compared to EU policy simulation levels)

happened under the implementation of the 140 g/km standard, be it that the order of magnitude is now larger.

Also the evolution of emissions under the enhanced standard shows a pattern similar to that of the original standard (see fig 4.24), be it that the order of magnitude is now smaller. This can be explained by a decreasing contribution of private cars in overall transport CO_2 emissions, hence any further reduction for this mode has a decreasing impact on overall emissions.

For the change in consumer surplus (compared to the 140 g/km fuel efficiency standard) we observe that under this scenario the reduction of fuel cost (corresponding to the decreased fuel intensity) requires relatively much more investment in other costs (see figure 4.25). As a result the loss in tax income for the government will be relatively smaller. Note that the net change in consumer surplus in 2020 is 2,5 times larger than under the 140 g/km scenario.

The total social cost is presented in figure 4.26. The loss in tax income (cost for the government) is now smaller (corresponding to the decrease in fuel intensity) but the much larger loss in consumer surplus results in a net cost to society that is much larger than for the 140 g/km standard. The impact of the new 120 g/km standard on external cost by emissions (see figure 4.26) is of a smaller order of magnitude compared to the loss of consumer surplus.

It is not surprising that the further reduction of fuel intensity beyond 140 g/km is relatively more costly while it contributes less to the reduction of

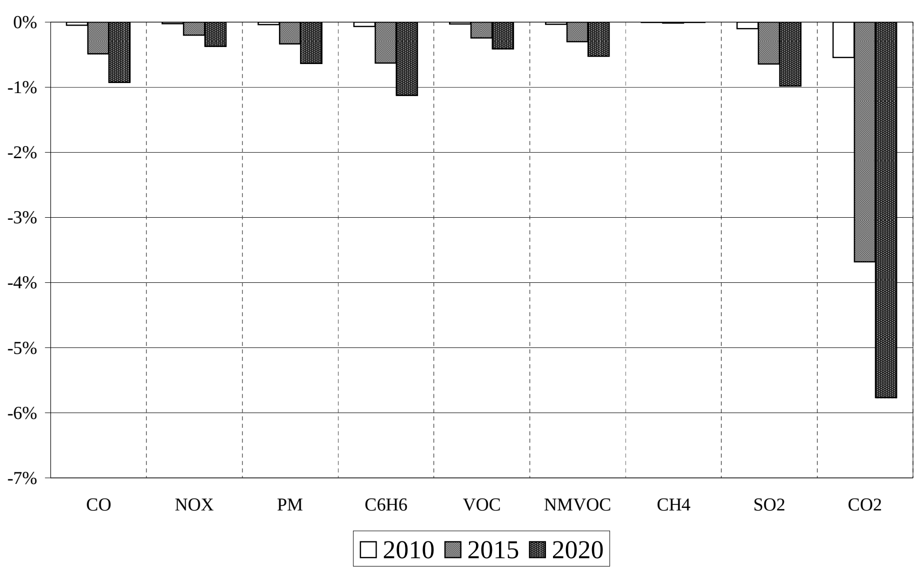


Figure 4.24. Impact of enhanced fuel efficiency standard on overall transport emissions (in % change compared to EU policy simulation levels)

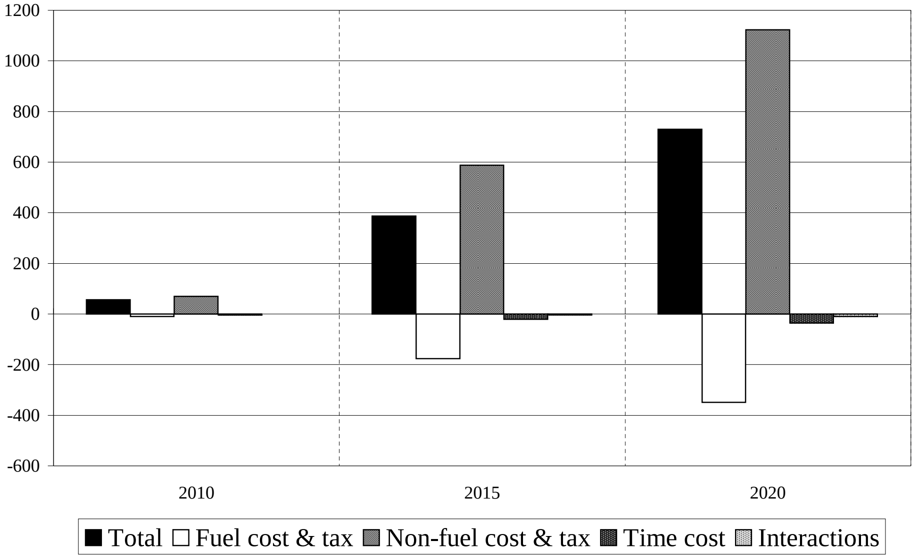


Figure 4.25. Decomposition of change in consumer surplus in passenger transport activity (in million €2000 compared to EU policy simulation)

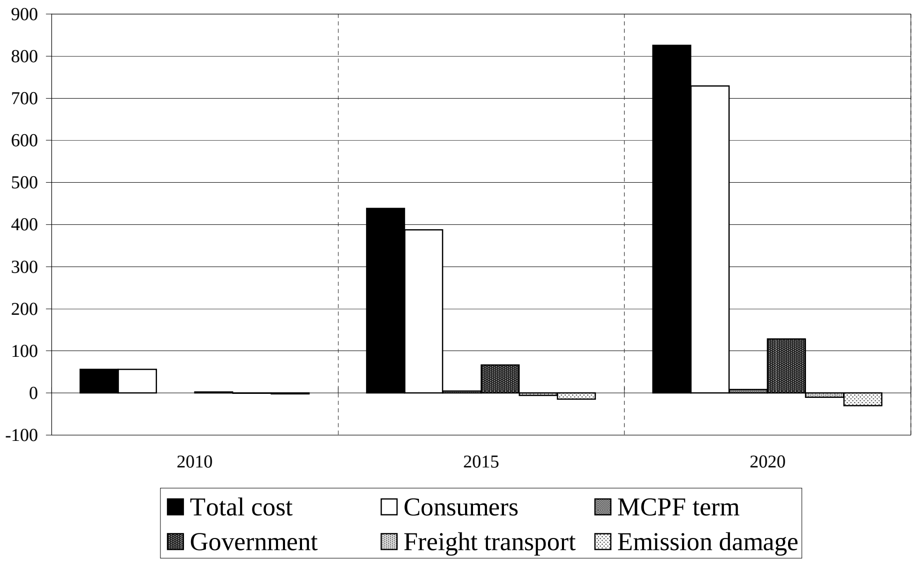


Figure 4.26. Annual welfare cost of enhanced fuel efficiency standard (in million €2000 compared to EU policy simulation)

emissions. This is reflected in the net reduction cost of 302 €/t of CO_2 in 2015. The 2005 net present value of the measure is 3182 million euro (compared to EU policy simulation) excluding the change in external emission cost. If we add the environmental gain to the account, the cost of the measure decreases somewhat to 3076 million euro.

CO_2 emission tax

In this section we simulate a substitution of the existing fuel taxes by a tax that is proportional to the marginal emission cost by CO_2 emissions. This tax is implemented from 2009 on and applies to all private cars, both new and existing, and follows the evolution of the external emission cost coefficient (see figure 4.10).[23] The level of the tax is optimised such that the net present value of reductions in external emission cost from transport CO_2 emissions over the modelling period (1995–2020) is identical to what is obtained by the enhanced efficiency standard.

The impact of the CO_2 taxation regime on fuel prices is presented in figure 4.27. Fuel prices go up by 50 to 100% in 2009 and then continue to rise in line with the evolution of the CO_2 external emission cost coefficient to reach a 2020 level that is above 2 €/l. It is quite obvious that this tolling scheme will have an impact—the tax mounts to about 40 times the external CO_2 cost, which already at this point provides us with an indication on what we may expect as net welfare result.

Interesting to note here is that whereas in the baseline diesel is cheaper than gasoline (on a volumetric base), the relative order switches under a CO_2 tax, meaning that the cost increase for diesel is relatively larger than for gasoline. This supports findings in chapter 3 that diesel technologies are promoted (over gasoline) under the existing taxation scheme and there seems to be no rationale to support such a setting. Similarly, De Borger and Mayeres (2004) find in their study on optimal taxes that efficient pricing requires substantial increases in the relative user tax on diesel cars as compared to gasoline cars.

The increase in fuel cost has an important impact on lifetime user cost (see figure 4.28). The user cost increase for medium engine size diesel technologies evolves from about 20% in 2010 to nearly 35% in 2020. The impact on gasoline technologies user cost is some percentage point smaller.

The evolution in fuel efficiency under this scenario is linked to the evolution of the fuel price (formula (4.4)). The resulting fuel efficiency is presented in figure 4.29. We observe fuel intensity levels which are typically above the 120 g/km standard (but under the 140 g/km standard). We remind the reader that the overall environmental cost of CO_2 emissions in the taxation

[23]For completeness we note that the non-fuel taxes are not changed under this simulation, including the registration taxes which are higher for diesel than for gasoline vehicles.

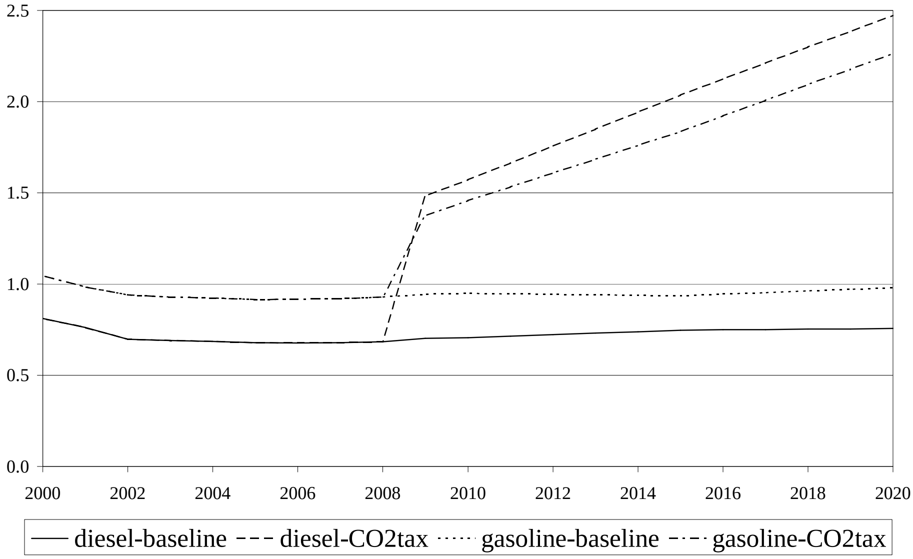


Figure 4.27. Impact of CO_2 tax on fuel price (inclusive taxes) for private car use (in €/l)

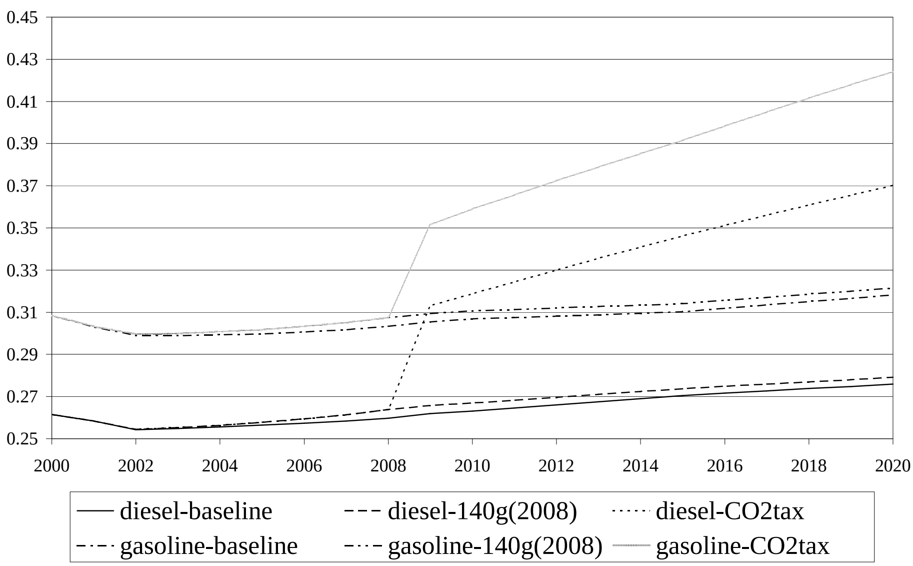


Figure 4.28. Impact of CO_2 tax on lifetime user cost of new private cars with medium engine size (in €/km)

simulation is identical to the 120 g/km efficiency standard scenario. As under the taxation scheme specific CO_2 emissions are higher than for the standard, we can expect that CO_2 emissions have been reduced in other ways (modal shift or global activity decrease). We also note that closer to the year 2020 fuel intensity comes closer to the enhanced standard. Apparently it is more efficient to postpone some of the reductions to a later point in the modelling period as the external cost coefficients are then larger (avoiding the same ton of CO_2 emissions then has a greater impact on inter-temporal external emission cost).

One could expect the impressive change in lifetime user cost to have a seizable impact on technology stock composition. This is however not the case (see figure 4.30). On the short run there is an adjustment of the stock (compared to the EU policy simulation levels) to the shock introduction of the increased fuel taxes in 2009: the shift from big towards small cars also includes a shift towards gasoline. In the period beyond 2009 fuel shares in new vehicle sales are not much different compared to existing EU policy simulations. What actually happens is that the logit choice functions in TREMOVE simulate technology shares based on absolute price differences. Up to 2012 the absolute increase in lifetime user cost is somewhat smaller for gasoline technologies so they increase their market share a little. By somewhere 2012 price increases for diesel and gasoline technologies of the same engine size are nearly identical, and beyond 2012 the absolute lifetime

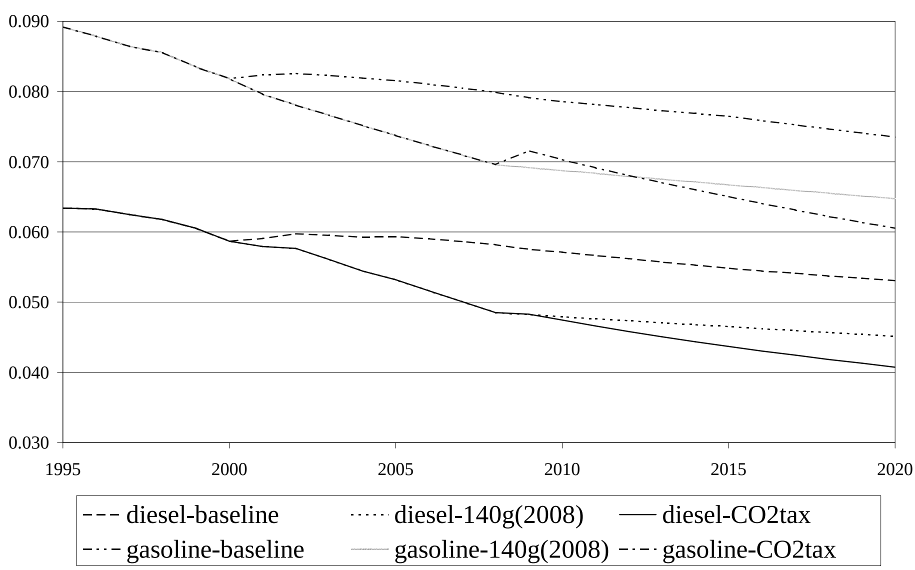


Figure 4.29. Impact of CO_2 tax on fuel intensity of new private cars with medium engine size (in l/km)

user cost increase is smaller for diesel technologies, resulting in an opposite shift in the stock.

Generalised prices follow technologies' user cost increase resulting in a large cost increase for private car transport activity (see figures 4.31 en 4.32). The corresponding modal growth rates are provided in figures 4.33 and 4.34. Note the 20% increase of transit demand in the Brussels metropolitan area. The higher service levels that come with the increase in public transport activity result in a decrease in waiting time cost and as a result there is an additional shift from non-motorised transport to public transport. In non-urban areas less substitution to public transport occurs. Overall passenger transport activity declines by 4,0% in 2020, whereas freight transport grows a very little.

Overall CO_2 emissions by transport activity (see figure 4.35) show a decrease of the same order of magnitude as in the efficiency standard scenario (see figure 4.24). However, also for the other pollutants the CO_2 tax results in a significant reduction. These reductions will have a far more important impact on the overall emission cost reduction as their external cost impact is large. The small increase in methane (CH_4) emissions reflects an increased demand for electrical energy by rail transport.

Studying the cost to society (see figure 4.36) we see that the net cost is lower than for the efficiency standard (figure 4.26). Consumers of passenger transport do face an important increase in costs, however most of this increase

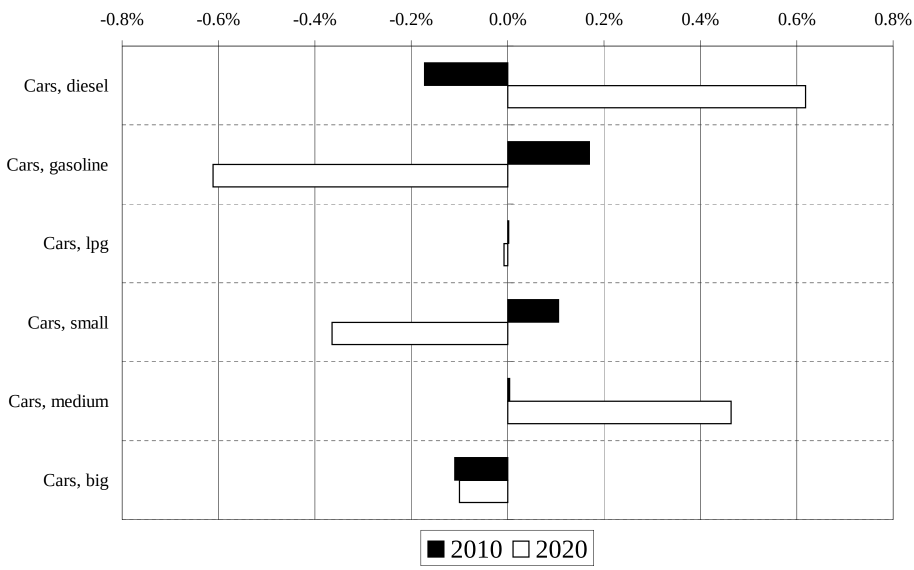


Figure 4.30. Impact of CO_2 tax on private car stock composition (change of technology share in percentage point compared to EU policy simulation levels)

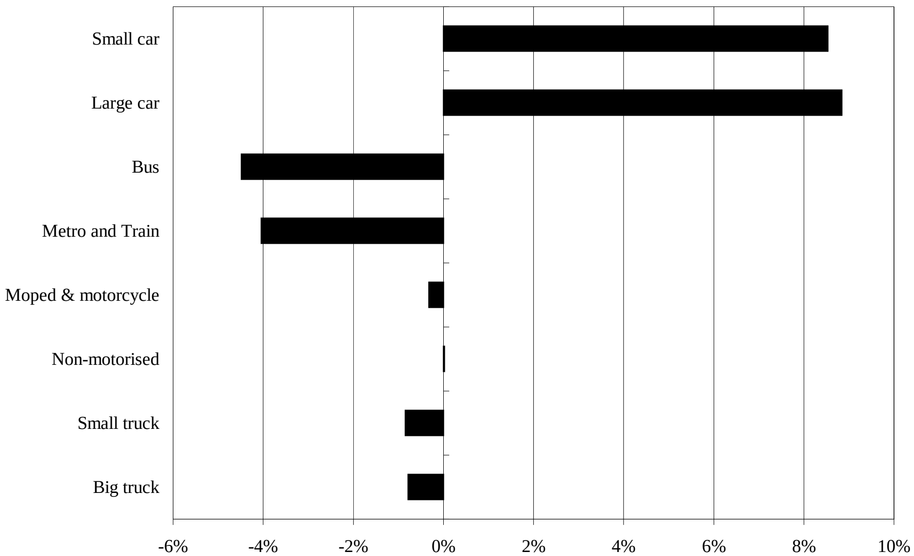


Figure 4.31. Impact of CO_2 tax on modal generalised prices in urban regions (in % change compared to EU policy simulation levels)

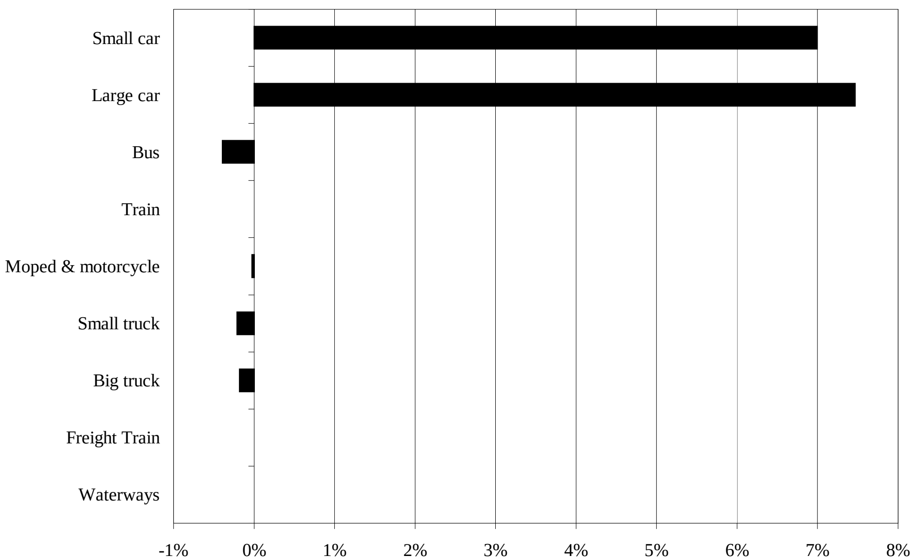


Figure 4.32. Impact of CO_2 tax on modal generalised prices in non-urban regions (in % change compared to EU policy simulation levels)

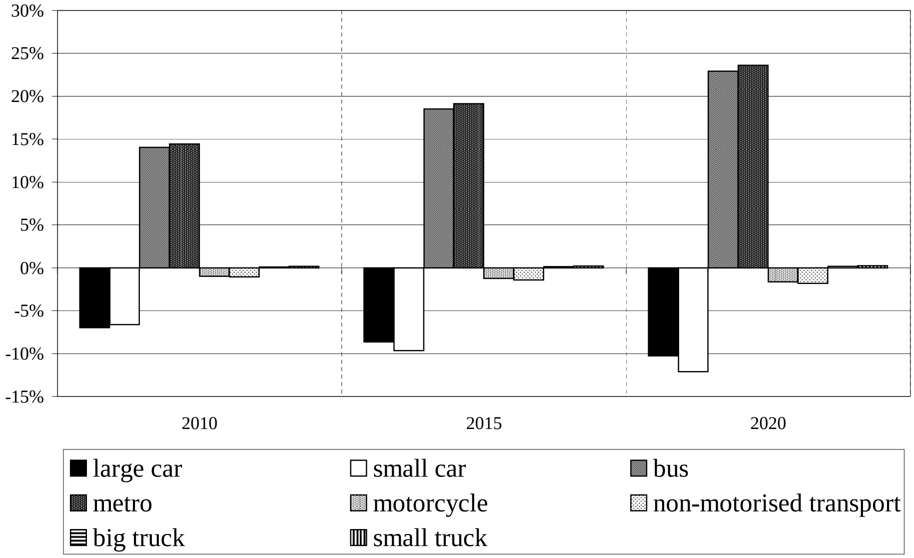


Figure 4.33. Impact of CO_2 tax on Brussels passenger transport activity (in % change compared to EU policy simulation levels)

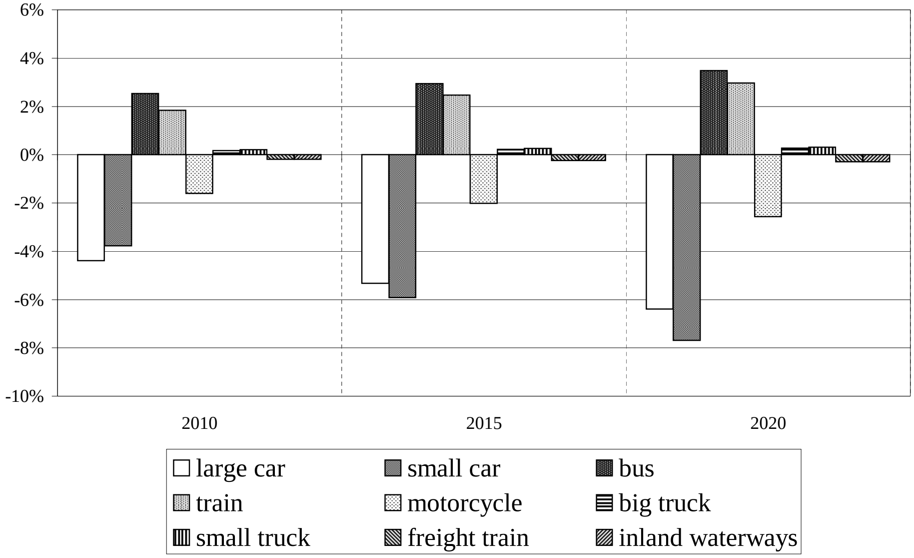


Figure 4.34. Impact of CO_2 tax on non-urban passenger transport activity (in % change compared to EU policy simulation levels)

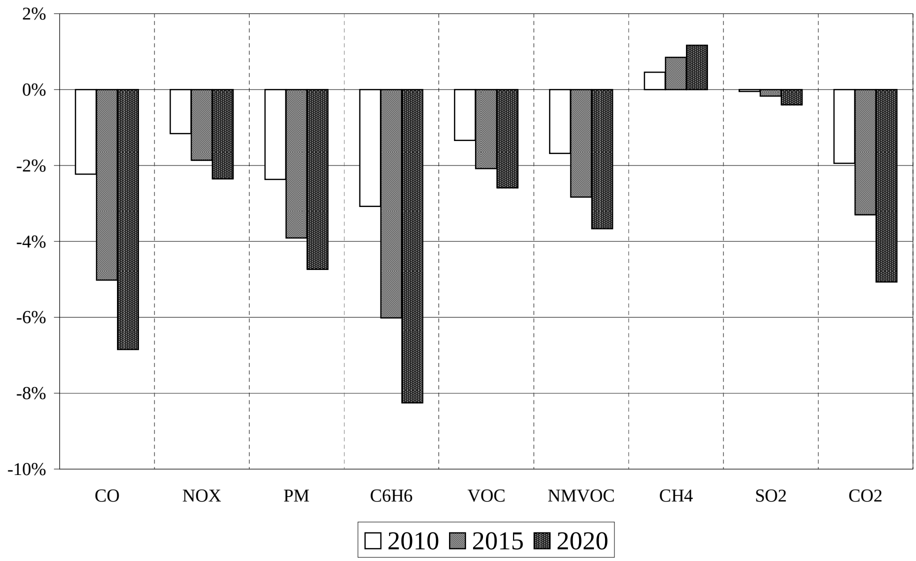


Figure 4.35. Impact of CO_2 tax on overall transport emissions (in % change compared to EU policy simulation levels)

is due to the fuel tax which can be recycled and hence does not result in a welfare loss.

The lower welfare cost is obtained by reducing CO_2 emissions by other means than a fuel efficiency improvement only. Comparing the tax scenario to the efficiency standard we observe that with the efficiency standard, passenger transport activity is too high from a welfare optimising point of view, requiring a too stringent efficiency standard in order to reach the overall emissions target. Moreover, under the efficiency scenario all reductions have to come from new private cars, whereas the emission tax allows us to target the existing stock as well.

The net present value of both the enhanced efficiency standard and the CO_2 tax is compared in table 4.2. We see that the efficiency standard comes at about double the social cost of the emission tax whereas the reduction in external cost from CO_2 emission is identical. This is reflected in the per ton of CO_2 reduction cost of 127 euro in 2015 (compared to 302 €/t for the enhanced fuel efficiency standard). Nevertheless, it still is a high cost compared to the external emission cost which is assumed to be in the 8–20 €/t range.

4.5. Caveats

In this section we discuss some limitations to our analysis.

First, *perfect competition* in car supply is an important assumption behind

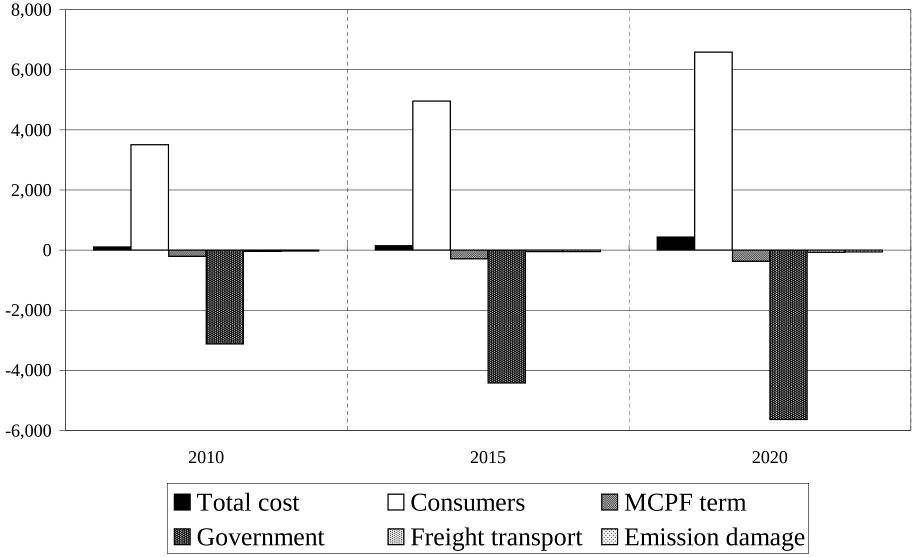


Figure 4.36. Annual welfare cost of CO_2 tax in million €2000 compared to EU policy simulation

Table 4.2. 2005 net present value of measures to further reduce transport activity CO_2 emissions in million €2000 compared to EU policy simulation

	enh. eff. standard	CO_2 tax
Social cost excl. external emission cost	3182	1759
Total social cost	3076	1380

our modelling of the relationship between fuel efficiency and resource cost. This assumption greatly simplifies the modelling framework, however as shown by Verboven (1996) this assumption is not generally valid.

A second limitation is the specification of the TREMOVE modelling framework that includes a fixed per car annual mileage assumption. As such we do not explicitly allow for a *rebound effect* that describes how increased fuel efficiency results in increased mileage per car.[24] Properly accounting for this effect may result in lower savings in CO_2 emissions for the emission standards scenarios, resulting in a higher per ton abatement cost.

A third caveat in our approach is the TREMOVE *technology choice model*. Two aspects of this nested logit choice model (see chapter 2 for its specification) may impact our results. At first there is some discussion on the price sensitivity

[24]For clarity we emphasise that the demand model used in TREMOVE does consistently account for all changes in user cost, including fuel cost and resource cost. The only limitation is that fixed costs (such a purchase cost and annual cost) are translated to a per kilometre cost using constant annual mileages per car.

of the diesel-gasoline share (see chapter 2). Given that the TREMOVE 2 technology choice model was designed to reproduce observed shares (in 2000),[25] a more price-sensitive model would result in larger changes in the market shares but would not affect the sign of the change. In the simulations we mainly observed a shift from gasoline to diesel. If this shift becomes bigger, this would contribute to the reductions of specific CO_2 emissions and hence require smaller contributions of technological improvements. The net result of a more sensitive technology choice model is thus likely to simulate a somewhat lower welfare cost of the measures (the reduction in CO_2 emissions being a fixed target).

A second aspect of the TREMOVE modelling specification applied in this chapter is that we do not study the availability of alternative fuels. As studied in chapter 3, some of these technologies have a rather good emissions record and might be able to contribute in a more cost-effective way (compared to conventional technologies) to a reduction in specific CO_2 emissions.

A last caveat in our approach to modelling fuel efficiency are the (indirect) *cost curves*, and more specifically the elasticity ϵ which is behind it. As we already indicated in section 4.2.1, cost curves may vary over engine sizes and fuels, further research is required to allow for a refinement of the curves. In a similar way, the rate of the autonomous progress (determining the reference point for the cost curves) may not be identical for all engine sizes and fuels.

4.6. Conclusions

The TREMOVE framework was selected as modelling tool for the assessment of the environmental and social impact of the EU policy regarding setting fuel efficiency (and CO_2 emissions) standards for new private cars. We successfully implemented an important extension to the model in order to allow for a comprehensive simulation of private car fuel efficiency as a function of fuel prices (including taxes).

The baseline evolution indicates that under a *business-as-usual* setting (and in the absence of a fuel efficiency policy) the gain in fuel efficiency is limited to autonomous technological progress (if any). This does not suffice to compensate for the growth in transport activity resulting in a net increase of overall CO_2 emissions.

A fuel efficiency standard for private cars allows to obtain a significant reduction in transport CO_2 emissions. We however show that such a reduction comes at too high a cost. It may be advisable to dedicate efforts to sectors where CO_2 abatement comes at a lower cost.

The comparison of the efficiency standard to a CO_2 tax for fuels used by private cars reveals that the tax reduces the cost to society by half compared

[25] The observed shares in 2000 determine the values of the technology-specific dummy coefficients in the technology choice model.

to the efficiency standard. The main reason is that an efficiency standard does not use reductions in the car use of new and of existing cars to reduce CO_2 emissions. A CO_2 tax optimally balances a reduction in private car transport activity necessary for a welfare optimisation.

CHAPTER 5

Bus transit and the environment

5.1. Introduction

Urban air pollution from transport activity receives a lot of attention in environmental and transport policy. In order to reduce pollution levels to improve urban environmental quality, several measures have been considered and implemented, ranging from cleaner transport technologies, pricing measures and even going as far as ruling out all car use during periods of heavy pollution. Apart from targeting private car activity directly, it is often considered to improve transit quality in order to have travellers shift to this transport mode that is considered to be cleaner.

Research on optimising transit supply historically focuses on optimal user price, service frequency and stop density. The seminal paper by Mohring (1972) defines the playing field for first best optimisation of urban transit operations. The key transit property identified are the economies of scale that exist in transit operations. In a subsequent paper, Turvey and Mohring (1975), while considering the stop density to be fixed, further iterate on the optimal prices and service frequency. The scope of the model is extended by Jansson (1993) who accounts for both urban and rural transit. All these models typically consider demand to be given rather than being a function of prices and frequencies. Moreover, the scope of operational costs is limited to internal costs only such as vehicle costs and driver wage, leaving out externalities.

Environmental externalities in urban transport activity are studied by Mayeres, Ochelen, and Proost (1996), identifying an external emission cost per vehicle kilometre for buses that is 15–20 times larger than for private cars. The comparison between cars and buses is studied in more detail by Romilly (1999), revealing that substituting bus for car travel may result in an increase in environmental damage costs. Both studies however are limited to a one by one comparison of a broad range of externalities per passenger kilometre and do not consider other social costs such as the impact on user cost or government budget.

To allow for a more comprehensive welfare assessment of urban transport policy measures, new models have been developed. These models typically cover the choice between two or more transport modes and a time of use decision. Most models consider an extended range of transport externalities and allow for an optimisation of decision variables under both first and second best conditions.

The model by De Borger, Mayeres, Proost, and Wouters (1996) includes three modes (private car, bus and rail) and two periods (peak and off-peak). The decision variables to be optimised are user prices only. Transit is modelled in a rather coarse way with fixed occupancy rates. An update of the model is presented in De Borger and Wouters (1998), now extending the scope to include transit supply decisions as well as road infrastructure supply.

A more detailed model is presented by Van Dender and Proost (2003). The TRENEN model simulates 30 transport markets covering all urban modes for two time periods. The transit sector is represented in a less detailed way, assuming fixed occupancy rates but allowing for economies of density.

A somewhat different look to the two-mode problem is presented by Kraus (2003). By combining the road transport bottleneck model (Arnott, Palma, and Lindsey, 1993) with a mass transit counterpart, they take an innovative approach to modelling the time of use decision. The decision variables covered include both user cost and transit supply.

A limitation of all these static models is the absence of a detailed vehicle stock representation. As discussed in chapter 3, the environmental impact of road vehicles is rapidly decreasing over time as new technology standards become mandatory. In order to allow for the environmental assessment of policy measures that have an impact on the vehicle stock composition, the TREMOVE model (version 1.3a) was developed (European Commission, Standard & Poor's DRI, and Katholieke Universiteit Leuven, 2000; European Commission, Transport Directorate-General, 1999). The representation of transport markets is similar to the TRENEN model (Van Dender and Proost, 2003) on which it was based. The vehicle stock turnover representation carries much detail for all road modes except buses. Transit (both rail and road) representation is somewhat summary, allowing for economies of density but assuming a fixed occupancy rate and no vehicle stock representation. Moreover, only emissions of road modes are modelled, limiting somehow the use of the model for transit policy simulations.

In this chapter we study the contribution that transit can make to a cleaner urban environment. In a first step we look how ticket prices and transit supply levels can be optimised and assess the net welfare and environmental impact of such a scenario. After optimising the pricing of transit, we have a further look to the potential contribution that can be expected from technical improvements. We consider two technical scenarios: one where older and more polluting bus vehicles are retrofitted to meet a more advanced emission standard and a second scenario where cleaner technological options are chosen for new buses that enter the vehicle stock.

The modelling framework that will be used to simulate the impact of different policy scenarios is that of the TREMOVE Brussels model. We start from the TREMOVE Belgium model that was implemented in chapter 4 and further extend it to allow for optimal pricing of transit and retrofitting of vehicles. A base case scenario for the Brussels area is designed to calibrate the model. The geographical scope of the simulations discussed in this chapter is hence limited to the Brussels metropolitan area.

5.2. Transit pricing, vehicle technology and the environment

The three operational variables that we will study in this chapter are the frequency, ticket price and vehicle technology. In the next sections we will discuss how their welfare and environmental impact can be studied and assess their potential to improve urban air quality. For completeness we note that other operational variables such as stop density do exist, however they fall beyond the scope of this study.[1]

For clarity we point out that, throughout this chapter, all cost values are expressed in constant prices of 2000, unless mentioned differently.

5.2.1. Optimal transit pricing and the environment

In this section we study how transit should be priced from a welfare point of view including external costs related to emissions. This section is based mainly on Mohring (1972) and Turvey and Mohring (1975), whose fundamental insights on optimising transit activity are extended here in order to include environmental externalities.

As noted by Mohring (1972), transportation differs from the typical commodity in that travellers play a producing and not just a consuming role: the generalised cost of a trip is determined by resource costs as well as time costs.

Contrary to other modes, time costs for transit users do not only depend on average vehicle speed, but also include waiting time and the time necessary to walk to the nearest stop. Increasing the frequency reduces waiting time cost but increases operating costs as well as emission levels. To minimise the total social cost of transit, an optimal frequency level needs to be determined. In a similar way the location of stops can be optimised, but as noted before this variable falls beyond the scope of this study.

[1]The framework of the TREMOVE model that we will use for policy simulations in section 5.4 is lacking the spatial dimension that is required for a comprehensive simulation of characteristics such as stop distance.

Another characteristic of transit is that an increase in transit patronage results in an increase in supply which means higher frequencies and hence a decrease in time costs for all users, both the new and the existing ones. Or to put it differently: the social marginal cost of transit activity is smaller than the average cost. Optimising welfare requires pricing at the marginal social cost level, which means in this case below the average cost, hence requiring subsidies. We study here how optimal pricing should be done when there also exist environmental externalities.

Optimal occupancy rates

The social cost of transit activity (in euro per pkm) can be formulated as:[2]

$$C = \frac{C_o}{D} + \frac{V_w}{2fL_t} + \frac{C_w}{L_t} + V_t T + \frac{C_e}{D} \tag{5.1}$$

where

- C_o is the operating cost in euro per vehicle kilometre (vkm)
- D is the average occupancy rate (in travellers per vehicle)
- V_w is the value of time during waiting (in euro per hour)
- f is the average frequency (in departures per hour per direction)
- L_t is the average trip length (in pkm)
- C_w is the walking cost from/to the stop
- V_t is the in-vehicle value of time (in euro per hour)
- C_e is the marginal external emission cost (in euro per vkm)
- T is the commercial travel time (in hour per km)[3]

The first term represents the operating cost of the transit network. The second term is the waiting cost, assuming an average waiting time of half the interval between two departures. The third term is the walking cost. The fourth term is the own time cost during the trip on the vehicle and the last term is the external emission cost.

At a given level of demand q, the required bus fleet size B follows directly from the occupancy rate D:

$$\frac{B}{T} = \frac{q}{D} \tag{5.2}$$

In a similar way, the occupancy rate D and frequency f are linked through the network length L_n for a given level of demand q:

$$q = Df2L_n \tag{5.3}$$

[2] We assume a *steady state* route. Mohring (1972) also discusses an alternative specification for a *feeder* route.

[3] Throughout this chapter T is the commercial travel time and $1/T$ is the transit commercial speed. It is the time/speed that reflects both travelling as well as calling at stops to allow travellers to (dis)embark. Technical operations such as turning times between different runs are however excluded.

where
- q is the level of demand (in pkm per hour)
- L_n is the network length (in km)

The factor 2 results from the definition of L_n:s in this study we assume all network links to be bidirectional. Using this relationship between f and D allows to express the social cost C as a function of occupancy D:

$$C = \frac{C_o + C_e}{D} + \frac{V_w D L_n}{q L_t} + \frac{C_w}{L_t} + V_t T \tag{5.4}$$

Optimising the occupancy rate[4] for a given demand level q now comes down to solving:

$$\frac{dC}{dD} = \frac{V_w L_n}{q L_t} - \frac{C_o + C_e}{D^2} + \left[V_t + \frac{1}{D}\left(\frac{dC_o}{dT} + \frac{dC_e}{dT}\right)\right]\frac{dT}{dD} = 0 \tag{5.5}$$

In the absence of transit congestion ($dT/dD = 0$), a closed expression for optimal occupancy rate D exists as pointed out by Mohring (1972). In the next section we will discuss the issue of transit congestion more in detail.

We do not specify here the relation between operating cost C_o or external environmental cost C_e and travel time T. Mohring (1972) limits C_o to a fixed cost per hour, but more detailed functional relationships seem to allow for a more realistic modelling of operating costs: part of C_o may be a function of mileage (e.g. maintenance costs) and hence is not a function of T, whereas another part is rather time-based (e.g. driver wages, capital costs) and still another part may have a mixed character (e.g. fuel costs where the fuel consumption is both a function of distance driven and speed). The same holds for C_e. In our model implementation we will discuss the functional relationship for both variables as implemented in TREMOVE.

Optimal ticket price

The focus of Mohring (1972) are the economies of scale that exist in bus transit. As the demand q increases, optimal frequencies also go up resulting in shorter waiting times and hence smaller generalised user costs. Or to put it differently: marginal social costs of a bus trip go down as demand goes up. This is a situation of increasing returns to scale.

To optimise welfare the user cost has to be equal to the marginal social cost.[5] We assume that there are, in the rest of the economy, no pricing distortions. To calculate the short run social cost, we assume that the number

[4] We repeat here for emphasis that through equations (5.2) and (5.3) occupancy rate, frequency and vehicle fleet size are linked. So optimising occupancy rate corresponds to optimising frequency and vehicle fleet requirements (and vice-versa) throughout this chapter.

[5] We note that under optimised frequency (or occupancy rate) short run and long run marginal social cost are equal.

of buses is fixed at B. Using relation (5.2) we can write the short run[6] social cost of a pkm as:

$$C = \frac{(C_o + C_e)B}{qT} + \frac{V_w T L_n}{L_t B} + \frac{C_w}{L_t} + V_t T \tag{5.6}$$

The social cost of an additional user is then:

$$\begin{aligned}\frac{d(qC)}{dq} = & \underbrace{\frac{V_w T L_n}{L_t B} + \frac{C_w}{L_t} + V_t T}_{\text{own time cost}} \\ & + \underbrace{\left[V_t + \frac{V_w L_n}{L_t B} + \frac{B}{qT}\frac{d(C_o + C_e)}{dT} - B\frac{C_o + C_e}{qT^2}\right] q \frac{dT}{dq}}_{\text{system cost}}\end{aligned} \tag{5.7}$$

The first three terms represent the own time costs of the user, the last term is the system cost: if the additional traveller causes a small decrease in speed, this has a social cost.

Van Dender and Proost (2003) study second best optimal pricing assuming no transit congestion ($dT/dq = 0$) using the TRENEN model which is an optimisation tool. In such a second best setting the optimal user price is function of distortions on other (transport) markets. In this study however we focus on first best pricing: what is the optimal transit price under the assumption of undistorted markets. In a next step we will use TREMOVE to simulate the impact of this first best pricing in the presence of distortions on other transport markets.[7]

In a first best setting, a no transit congestion assumption seems unrealistic as equation (5.7) shows that it leads to a zero optimal ticket price (when $dT/dq = 0$ the system cost that is not paid by the user is zero). We therefore use the transit congestion function proposed by Mohring (1972):

$$T = \frac{1}{S} + \frac{2D}{L_t}\epsilon + \frac{\delta}{d}\left(1 - e^{-\frac{2D}{L_t}d}\right) \tag{5.8}$$

$$\Rightarrow \frac{dT}{dD} = 2\frac{\epsilon + \delta e^{-\frac{2D}{L_t}d}}{L_t} \tag{5.9}$$

where:

- S the no-travellers speed[8]

[6]The difference between the short and long run is the possibility to adapt the size B of the vehicle fleet (we follow here the setting discussed by Turvey and Mohring, 1975). The long run optimal vehicle fleet size is determined by the optimal occupancy rate as expressed by (5.5).

[7]For clarity: TREMOVE is a simulation tool and does not allow to optimise for second best constraints.

[8]In the evolution of the baseline (section 5.3.2) and in the simulation of transport scenarios (section 5.4) the value used for S will reflect the level of road congestion as illustrated in figure 5.6.

- δ the time (in hours) necessary to slow down, open and close the doors and to re-accelerate at a stop
- ϵ the time (in hours) necessary to let a user embark/disembark
- d the average stop distance

The first term in equation (5.8) is the travel time without travellers. The second term represents the time necessary to let the travellers embark and disembark the vehicle. The last term represents the time necessary to make an additional stop. This last term is not proportional to the number of travellers, as an additional stop is only required if no other traveller wants to embark/disembark at a stop. We note that in metro or train operation δ is zero, considered that the vehicle does always call at all scheduled stops, independent of whether travellers actually want to embark or disembark.

Substituting B (expression (5.2)) in equation (5.7), the ticket price C_m (in euro per pkm) should be equal to:

$$C_m = \left[V_t + \frac{V_w L_n D}{q L_t T} + \frac{1}{D}\frac{d(C_o + C_e)}{dT} - \frac{C_o + C_e}{TD}\right] q\frac{dT}{dq} \tag{5.10}$$

where

$$q\frac{dT}{dq} = \frac{2TD\left(\epsilon + \delta e^{-\frac{2D}{L_t}d}\right)}{TL_t - 2D\left(\epsilon + \delta e^{-\frac{2D}{L_t}d}\right)} \tag{5.11}$$

The first term in equation (5.10) represents the increase of in-vehicle time costs of all travellers caused by the additional user. The second term expresses the impact of the additional user on the waiting costs of all travellers at the bus stop. The third term represents the impact of a change in speed dependant operating and environmental costs (for instance the wage of the bus driver), whereas the last term represents the decrease in vehicle mileage caused by the additional user (remember that the fleet size is fixed at B).

Let us have a closer look at the impact of the operating and environmental cost ($C_o + C_e$) on the ticket price C_m (equation (5.10)). At first it may seem odd that the reduction in vehicle mileage caused by the traveller reduces the optimal ticket price he or she faces. However, for costs that are purely time related (such as the driver wage), both terms cancel out (a finding in line with Mohring, 1972). Indeed: the number of drivers needed is a function of the fleet size B which is fixed here (short run condition), so the level of the drivers' wages has no impact on optimal ticket prices. At the other hand, an increase in purely distance related costs does reduce optimal ticket prices. But as noted by Turvey and Mohring (1975), such an increase has also an impact on the long run optimal fleet size (equations (5.2) and (5.5)). Under such conditions the optimal occupancy rate D increases, which in turn leads to fare increases.

Peak load pricing and optimal fleet size

Equations (5.5) and (5.10) express how occupancy rate (and corresponding vehicle fleet) and user prices are optimised for a given demand intensity level q expressed in passenger kilometre per hour. In transit provision it is however common that demand intensity levels vary over time. For this study we will differentiate demand intensity over two time periods: peak and off-peak.

Optimising occupancy rates and ticket prices for different time periods calls for an integrated approach. The vehicle fleet size is determined by the period with the highest demand level. As a result it is appropriate to set ticket prices higher during peak periods (to manage fleet-determining demand) and lower during off-peak (when the peak-dimensioned fleet is available anyway and as a result there is no marginal capital cost in service production).

We will limit the discussion here to the case where off-peak transit supply does not make use of the entire fleet (hence in the equilibrium a strictly positive number of vehicles are redundant for off-peak operations).[9] The fleet size is in that case determined by characteristics of peak operations only and follows from formula (5.5) applied to peak demand. As discussed by Williamson (1966), the peak demand should then bear the entire burden of vehicle fleet capital costs. The approach of attributing capital costs to the peak demand period is known as *peak load* pricing.

The Brussels metropolitan area

Different transit operators are active within the borders of the Brussels Capital region. Heavy rail is operated by NMBS, light rail (metro and tram) by MIVB and bus by MIVB, De Lijn and TEC. None of these operators limit their operations to the Brussels area, and reported activity figures are usually not split up geographically. It is however obvious that the main share of activity by MIVB is on the Brussels territory and for simplicity we mainly use figures reported in their annual reports[10] to represent Brussels transit activity.

The framework of the TREMOVE model, that we will use for our policy simulations, accounts for only one rail mode, rather than the three different networks that are present in the Brussels metropolitan area (tram, metro and train). In most cases adding up the characteristics of the three networks is rather straightforward in order to determine parameter levels for the rail mode representation in TREMOVE. This composite rail mode is nevertheless somewhat abstract in some characteristics, e.g. average speed is a somewhat intangible characteristic given that travellers travel faster than vehicles do on

[9] This condition has been checked to apply throughout baseline and scenario simulations in sections 5.3.2 and 5.4.

[10] Maatschappij voor het Intercommunaal Vervoer te Brussel [MIVB] (2004, 2005) provides base year figures for the 2002–2004 period. Throughout this section we will only provide approximate figures based on these three base years, exact figures for each of the three years are available from the author.

average. We will have to simplify in order to fit rail transit activity in the TREMOVE framework.

Trip length L_t, network length L_n and stop distance d The MIVB average trip length L_t is about 5,08 km. We assume this trip length to be constant over modes (bus/rail) and periods (peak/off-peak). Together with the reported number of travellers we obtain the passenger kilometre activity, which for bus covers about 94% of total baseline activity (see section 5.3.2 for a discussion of baseline activity). We assume the remainder of the market to be equally shared between De Lijn and TEC. We assume the L_t value to apply to the other operators as well, as we do not have separate figures for them (NMBS for rail and De Lijn and TEC for bus).

Network length L_n reported by MIVB is about 350 km for bus and 167,5 km for light rail. For heavy rail a number of 163,2 km is reported by Studiedienst van de Vlaamse Regering (2006). Network length here is not equal to the sum of the length of the transit lines, as different lines may share a common network link. For train the figure seems somewhat high, it may be that freight-only diversion lines are included. At the other hand the same railroad stretch may be operated by intercity as well as local trains, which could be considered as sufficiently different to allow for some double counting. For De Lijn and TEC we have no figures, we decide therefore to assume identical occupancy rates and frequencies and adapt the MIVB bus network length figure accordingly. Averages stop distance d for light rail and bus is based on annual reports by MIVB, for heavy rail we use annex 10 of the network statement 2005–2006 by the Belgian rail network operator (Infrabel, 2005) to calculate a figure of 2167 metre.[11]

Adding up different rail modes we obtain a network length L_n of about 330 kilometre and an average stop distance d of about 1300 metre for the composite urban rail mode.

Calibrating the transit congestion function (equation (5.8)**)** Values for δ and ϵ for bus transit are based on Mohring (1972). For rail operation we assume δ to be zero, which obviously holds for heavy rail and metro where all scheduled stops are called at independently of travellers' intentions to (dis)embark but is somewhat less realistic in tram operations where some scheduled stops are called at upon request only. A value for ϵ is calibrated using metro commercial speed observations ($1/T$) for different periods and linking them to differences in baseline transport demand (q), obtaining a value of 0,17 to 0,21 s. The assumption is here that no other sources of congestion exist, an assumption that seems realistic in metro operation. We use the metro figure for the composite rail mode.

[11] This number is a rather rough approximation, it is however of minor importance considered that we will not study the impact of a change in this parameter.

The value for the no-travellers speed S is calculated using the values of δ and ϵ. For bus we use observed commercial speed ($1/T$) figures for different periods together with baseline flows (q). For rail speed is a somewhat complex issue: the composite rail mode mixing up tram, metro and train ends up in average travellers travelling at higher speeds than vehicles do, considered the smaller observed occupancy rate of the slowest vehicles (tram). We decide to deliberately simplify the matter and to calculate S from representative commercial speed values ($1/T$) provided by TREMOVE 2 (G. De Ceuster et al., 2005) for Brussels rail activity and baseline demand q.

Walking cost C_w and other time costs The level of the in-vehicle value of time V_t is based on values provided by TREMOVE 2. Past research indicates that value of walking and waiting time is higher than in-vehicle time, suggesting factors up to 12 (Wardman, 2001). In this study we decide to stick to a value of 3 times the in-vehicle value of time V_t as applied by Mohring (1972) for both walking and waiting time: $V_w = 3V_t$.

Walking costs C_w are calculated as the time necessary to cover half the average stop distance d at a walking speed of 4,2 km/h (speed figure based on TREMOVE 2): $C_w = V_w d/4{,}2$. This may seem to be a rather rough approach but as stated before, changes in walking cost C_w are not the focus of this chapter.

Operating cost C_o The marginal operating cost C_o per vehicle kilometre has to be specified for both modes (bus/rail) and time periods (peak/off-peak). In this study we follow an approach much similar to Peirson and Vickerman (2001). It mainly boils down to excluding sunk costs and attributing capital costs to the peak period. The rationale is that sunk costs have nothing to do with marginal operating costs and that the vehicle stock is dimensioned for peak operations, hence marginal operating cost in the off-peak period should not be affected by capital costs.

As indicated in the discussion on peak load pricing, the practise of attributing the full burden of capital costs to the peak period is optimal only in the case where there off-peak transit supply does not make use of the full fleet size.

It should be noted that identifying marginal operating costs is not straightforward. Available data sources are limited and available cost figures are not always well specified, e.g. it is sometimes unclear in how far infrastructure maintenance costs are related to actual use or merely sunk costs. It is suggested by Peirson and Vickerman (2001) that, in transit operation, large economies of scale exist, e.g. for urban rail transit marginal operating costs may amount to only 20 to 50% of average operating cost. This leaves much space for misspecifications.

The marginal operating costs as defined in this chapter consist of fuel costs, repair and maintenance costs, driver wages and capital costs (peak-only). Driver wages and capital costs are not distance related but rather time related. Reference scenario per vehicle kilometre costs are provided as an illustration in section 5.2.2.

For bus transit the diesel/CNG fuel cost will be determined endogenously in our simulations by the TREMOVE stock turnover module using stock composition and commercial speed ($1/T$) as an input to calculate average fuel efficiency using the COPERT III methodology (Ntziachristos and Samaras, 2000). Capital costs as well as repair and maintenance costs are also provided by the TREMOVE vehicle turnover module. Driver wage cost is fixed at 19,8 €/h (Uythethofken, 1998).

Marginal operating costs for rail are based on cost figures provided by different sources: Uythethofken (1998) for tram and metro and De Maesschalck (2004) for rail.

Environmental cost C_e The marginal external emission cost C_e of transit activity is calculated by multiplying emission factors with external cost coefficients.

Bus transit emissions are based on the COPERT III methodology (Ntziachristos and Samaras, 2000). The per vehicle kilometre emissions E are a function of commercial speed $1/T$:

$$E = a \left(\frac{1}{T} \right)^b \tag{5.12}$$

with a and b technology specific parameters provided by COPERT III.

For rail transit we assume the entire Brussels rail network to be electric. This is a realistic assumption: all tram and metro operations are electric, and for trains only a handful of diesel trains run on Brussels territory: diesel train operations are strictly limited because of tunnel railway stations on all Brussels rail lines. Electricity consumption factors for tram, metro and train are collected from the TREMOVE 2 documentation (G. De Ceuster et al., 2005). The obtained average electricity consumption factor for 2005 is 6,33 kWh per vkm.[12]

In a final step the electricity consumption is translated to emissions by using average electricity production emission factors provided by TREMOVE 2.[13]

[12]Note that in our model (see section 5.3) there is no explicit representation of vehicles for non-road modes. As such the only relevance of the electricity consumption factor quoted here is in combination with average vehicle occupation rates. The implicit assumption is that the relative shares of tram, metro and train in the composite rail mode are constant in the scenario simulations.

[13]We should stress some important assumptions that are behind the approach applied here. First we assume that transit is consuming the average electricity mix, which may not be fully

The external emission cost coefficients relate emissions from transport activity to external impact. A state-of-the-art overview of environmental external costs methodology is provided in Friedrich and Bickel (2001). In this study we decide to apply external cost coefficients from the TREMOVE 2 model, we present them in table 5.1.

The marginal external cost coefficient of VOC emissions is not differentiated over methane (CH_4) or benzene (C_6H_6) components[14], although actual external cost of the VOC emissions do differ (Friedrich and Bickel, 2001). However, the information on the composition of VOC emissions from rail transit activity is rather limited and hence it seems better to stick here to the single external cost coefficient for VOC emissions.

5.2.2. Cleaner bus technologies

In the previous section we discussed optimal transit pricing. Apart from pricing and service level policies, also technological improvements can be considered to improve environmental performances of bus transit.

Contrary to common opinion, bus transit using diesel technologies is not necessarily better for the environment compared to other modes. In figure 5.1 we compare the impact of emissions of different modes for both peak and off-peak periods under baseline conditions (for the baseline see section 5.3.2; the baseline occupancy rates are presented in table 5.3). In off-peak conditions, bus transit is the most polluting mode in 2010. When by 2015 and 2020 older polluting buses are replaced by cleaner Euro 5 compliant vehicles, external emission cost will be reduced by over 50%. However, under all simulated conditions small cars are still less polluting than buses. The

realistic considered peaks in demand. A second more important assumption made here is that all emissions from electricity production are emitted in the Brussels region, whereas it is possible that production is in far-away rural areas.

[14]The external cost difference between CH_4 and non-methane VOC (NMVOC) emissions in table 5.1 results from a difference in climate change impact only.

Table 5.1. Marginal external emission cost coefficients in € per ton (source: TREMOVE 2)

Pollutant	1995	2000	2010	2020
CO	3,15	3,15	3,15	3,15
NO_X	14000	14000	14000	14000
PM	540000	540000	540000	540000
NMVOC	7100	7100	7100	7100
CH_4	7284	7284	7376	7560
SO_2	31000	31000	31000	31000
N_2O	2368	2368	3552	5920
CO_2	8	8	12	20

relative environmental advantage of small cars over big cars is linked to the assumption that small cars are mainly gasoline fuelled, whereas for big cars diesel engines have an important share. Finally we note that rail is very clean. We add however that nuclear energy has a large share in Belgian electricity production and that external cost here is limited to cover emissions only.

In this section we provide a short introduction on two technological approaches that are considered by transit operators to reduce environmental impact of bus transit operations.

CNG technology for new bus vehicles

A first possible technological improvement is a fuel switch towards compressed natural gas (CNG). Many transit operators have experimented with this technology, e.g. MTA in Los Angeles county where CNG technologies have a large share in the vehicle stock but also MIVB in Brussels is operating 20 CNG-fuelled buses. A switch to CNG technology reduces emissions for most pollutants by a substantial amount compared to conventional diesel technology (see table 5.2).

Emission factors for CO, VOC, NO_X and PM are based on Hickman et al. (1999). Values for NMVOC and benzene are not available. We can however calculate similar factors for light duty vehicles (LDV) based on correction factors for gasoline LDVs (Hickman et al., 1999) and the baseline emission factors for gasoline and diesel LDVs which are mainly COPERT III based. We

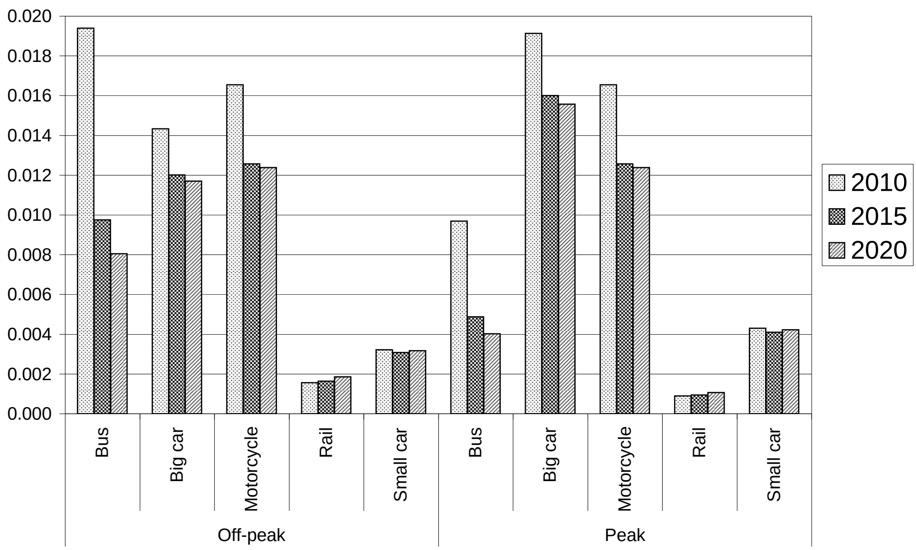


Figure 5.1. Baseline marginal external emission cost from passenger transport activity (in €/pkm)

assume the obtained factors to hold for heavy duty vehicles as well.

The difference in emission factors between diesel and CNG bus technologies corresponds to a reduction in external emission cost of 30 to 35%, depending on the reference diesel technology (Euro 4 or Euro 5).[15]

However, the switch to CNG comes at a cost. Apart from a (sunk) capital cost to adapt refuelling and maintenance infrastructure (not considered here), also the buses themselves are more expensive, as well as the fuel. The cost components required for the calculation of the marginal operating cost increase are mainly based on Vrije Universiteit Brussel, ETEC (2001), which reports data mainly from an actual CNG bus experiment by MIVB in the Brussels region.

The CNG fuel price excluding taxes is €0,69 per m^3 (37,1 MJ/m^3, which is an energy content similar to a litre of diesel fuel) in 2001. Energetic efficiency of CNG technology is assumed equal to diesel buses.

Capital cost (purchase cost) of CNG buses is assumed to be 20% higher than for conventional diesel technology (Verbeiren et al., 2003). Annual repair and maintenance costs are also 20% higher (Vrije Universiteit Brussel, ETEC, 2001).

The expected lifetime for CNG buses is assumed somewhat shorter than for diesel buses based on Verbeiren et al. (2003). We note however that this external assumption has only a small influence on stock turnover considered that most scrapping is determined endogenously in TREMOVE.

Full details on CNG technology characteristics are provided in appendix D.

Retrofitting existing bus vehicles

New technologies have the drawback that it takes some time until they get a seizable stock share, due to stock turnover which is rather slow for buses: the realised lifetime of the vehicles is typically about 15 years. An alternative approach hence consists in retrofitting older (more polluting) vehicles in order

[15]For Euro 3 the difference is 60%

Table 5.2. Emission correction factors for bus CNG technologies (reference is a diesel bus)

Pollutant	Factor	Source
CO	0,464	MEET-project (Hickman et al., 1999)
VOC	3,38	MEET-project (Hickman et al., 1999)
NO_X	0,583	MEET-project (Hickman et al., 1999)
PM	0,085	MEET-project (Hickman et al., 1999)
NMVOC	0,5	own calculation (see text)
C_6H_6	0,015	own calculation (see text)

to meet more stringent emission standards. Figure 5.2 provides an overview of the environmental impact of subsequent emissions standards for both vehicles and fuels. There is obviously some environmental potential in retrofitting recent buses.

Technology is available to upgrade Euro 2 to Euro 5 standards. Although it is difficult to obtain exact cost figures, such a retrofit may come at a per vehicle cost of €22500 and result in an additional operating cost of €0,05 per vehicle kilometre as a result of increased repair and maintenance cost and ureum consumption.[16]

5.3. TREMOVE Brussels

The focus of this chapter is to evaluate the contribution bus and rail transit can make to a reduction of overall urban transport emissions, and the related welfare impact of this environmental improvement. To allow for such an assessment we need a modelling tool that represents all transport markets, includes a vehicle stock representation, has an emissions module and translates impacts to welfare costs. The TREMOVE Belgium model provides most of

[16]Rough cost figures were quoted at a workshop by RET (Rotterdam urban bus transit operator). It is unclear how precise these amounts are given the competitive character of the Dutch bus transit operating market. We provide them here as an illustration. Note that the baseline assumes a cost increase for new diesel bus vehicles of €15000 between 2005 and 2010 based on Verbeiren et al. (2003), which roughly corresponds to the shift from Euro 3 to Euro 5 emission standards.

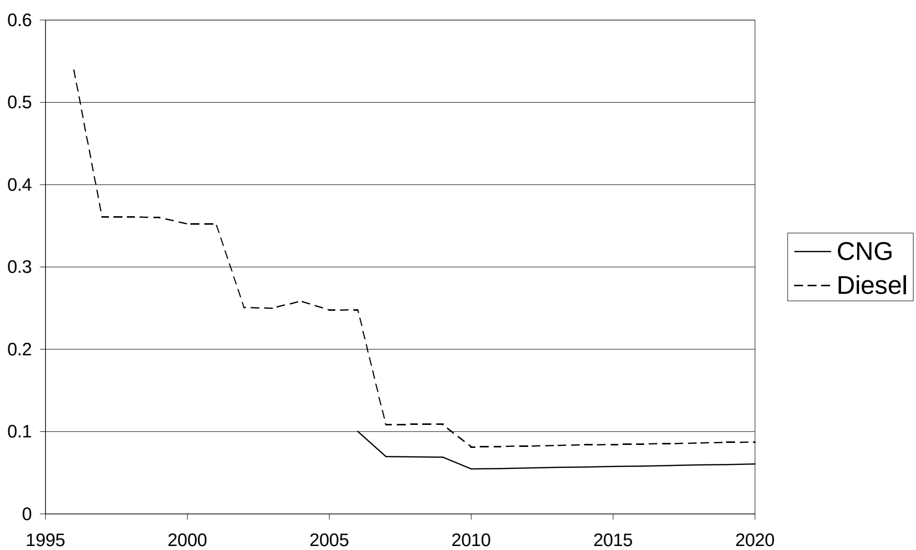


Figure 5.2. Baseline evolution of external emission cost by new vehicles (in €/vkm)

the features we need (see figure 5.3). An overview of the TREMOVE Belgium model specification is provided in appendix C.

In this section we discuss the implementation of the first best optimal frequencies and ticket prices, as well as the introduction of advanced bus vehicle technologies in the TREMOVE modelling framework. This allows to assess the environmental impact and the corresponding social cost of transit policy measures.

The assessment of the impact of policy measures on social welfare is the sum of changes in consumer surplus (passenger transport), producer surplus (freight transport), government income (taxes) and external emission cost.

We want to repeat here that the optimisation of frequencies and ticket prices presented in section 5.2.1 is a first best approach, this means that it optimises welfare when no distortions exist in other markets. It is however obvious that this is not always the case. But the framework of the TREMOVE model does not allow for the optimisation of any variable given the existence of distortions (second best approach)—simply because TREMOVE is not designed as an *optimisation* tool but rather as a *simulation* tool. In the scenarios we will therefore split external emission cost and government income between a transit-related term and the rest.

5.3.1. The model

We use the Brussels metropolitan area representation of the TREMOVE Belgium model as implemented in chapter 4 as a starting point for the TREMOVE Brussels model. We implement the first best optimal frequencies and ticket prices as discussed in section 5.2.1—this is fairly straightforward.

The implementation in TREMOVE of a technology shift to CNG buses does not require any special extension of the model.

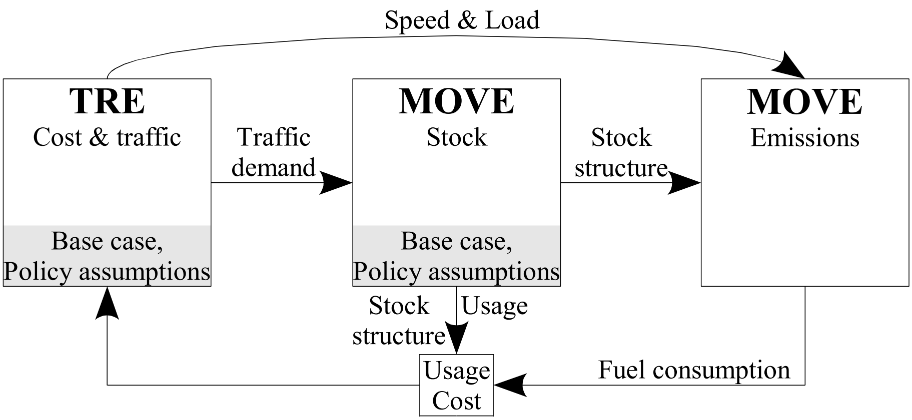


Figure 5.3. The TREMOVE Belgium modelling framework

As for the retrofit, we include two additional cost components. The first cost component is the capital cost of retrofitting the buses which is attributed to peak operations, the second component reflects additional repair and maintenance cost as well as ureum consumption and is defined as a per vehicle kilometre cost. For completeness we note that the retrofit cost components do not enter the endogenous scrapping model, i.e. the retrofit operation as modelled here does not influence the economical vehicle lifetime.

5.3.2. The base case scenario

The TREMOVE Belgium model provides a base case scenario for the Brussels metropolitan area that is used to calibrate the model. The base case scenario is a business-as-usual transport activity evolution that is considered as an input to the model. This baseline evolution should reflect what happens to the transport markets in case all decided transport measures are implemented but no new policy initiatives are added. In this section we revisit some aspects of the baseline in order to match the transit policy focus of this chapter.

Full details on the baseline are available with the author, we will limit here to a presentation of selected indicators that provide a global impression of baseline activity.

Base case transport demand

As a starting point we use the Brussels metropolitan area of the TREMOVE Belgium model implemented in chapter 4. Our special focus in this chapter on transit scenarios requires a review of selected baseline transport demand categories. A first one is the split up of transport activity over peak and off-peak. Whereas in the previous chapters the main motive for this split was to get a consistent representation of road network congestion, in this chapter it heavily influences peak load pricing of transit and as such the split should reflect peaks in bus and rail fleet usage. A second one is the split up of transit activity over bus and rail modes where a minor issue arises when applying baseline evolution to base year statistics.

In TREMOVE Belgium peak transport demand (in pkm or tkm) has a rather small share in overall activity (less than 20%). Considered that peak demand is denser than off-peak and that 90% of traffic the flow occurs in the period 6h–22h (Marcial Echenique & Partners Ltd, 1999), this peak demand corresponds to a time period of about 3h (240 days per year). In the modelling of urban transit we feel the need for a more extended peak period: capital costs are attributed to peak activity and based on MIVB (2004, 2005) the peak in vehicle operation is observed during about 6 hours per day. We therefore decide to double the peak activity and reduce off-peak activity accordingly.

Special attention is paid to rail transit. The (urban) rail mode in TREMOVE is in fact kind of a composite mode that covers light rail (trams, metro) and heavy rail (train) operations (see section 5.2.1). Based on annual reports from the operators we review activity levels of the different rail technologies for some base years. The baseline evolution of the different rail modes beyond the statistical period is based on the TREMOVE 2 baseline which provides a separate evolution for light and heavy rail operations. Only in a final step the different rail modes are taken together and used to calibrate the TREMOVE Brussels model. We use the separate light and heavy rail baseline evolutions to determine the level of other characteristics of the composite rail mode. Finally, to account for the higher rail activity in later years of the modelling period, bus activity is decreased somewhat in order to keep total transit activity constant for each year.

In a last step the evolution of transport activity over the historical period is brought in line with statistical information where available (mainly up to 2002). The final baseline transport activity evolution is presented in figure 5.4.

We observe the highest growth rate in freight transport. A small increase in road passenger modes is foreseen, whereas a negative growth is projected for non-motorised and rail passenger transport activity.

The calibration of a linear speed-flow network congestion function is based on TREMOVE 2 average speed figures.

The TREMOVE Belgium framework models urban transport activity for two separate groups: inhabitants and commuters, a specification that is not available from the TREMOVE 2 baseline. The number of commuters is assumed as 0,5 million in 1995. The number of inhabitants as well as the

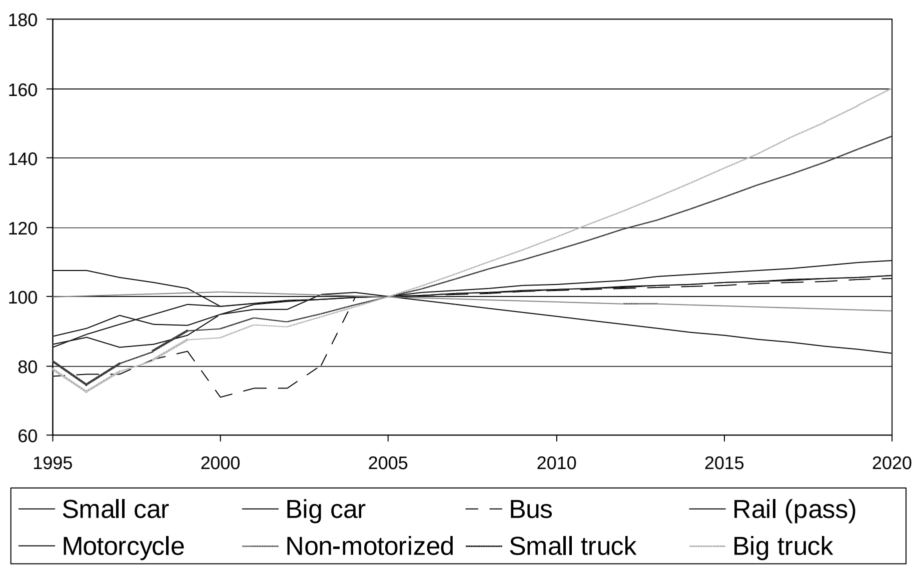


Figure 5.4. Baseline evolution of transport activity demand (index: 2005 level = 100)

evolution of the size of both groups is based on the TREMOVE 2 baseline. In order to attribute transport activity to both groups, we decide to split commuting and business passenger transport proportionally over both groups, the remaining transport activity is by inhabitants only.

Base case stock composition and emissions

The stock turnover module is calibrated by providing a base year (1995) stock composition. For all modes except buses we use the TREMOVE 2 base year stock figures for Belgium and scale them proportionally to the Brussels share in baseline vehicle kilometre activity.

For buses, we first calculate the annual number of peak hour activity per vehicle based on vehicle activity (in vkm), commercial speed and vehicle stock size figures from annual reports by the operator MIVB (MIVB, 2004, 2005). Based on this per vehicle peak-time activity we calculate the size of the stock necessary to cover baseline 1995 activity and scale the TREMOVE 2 base year stock accordingly. It should be stressed here that the base year stock composition (over vehicle ages) does not reflect any actual observation of the Brussels bus stock, but rather the different vehicle ages are assumed to have the same share in Brussels as they have in overall Belgian vehicle registrations.[17]

The stock composition beyond the base year is generated by the stock turnover module of the TREMOVE model. The baseline stock composition together with transport activity allows for the calculation of baseline emissions as presented in figure 5.5. We observe a strong decrease for most pollutants, reflecting incremental emission technology standards that are implemented up to 2008 (Euro 5 for heavy duty vehicles) as well as fuel standards (e.g. sulphur free fuels). We note a decrease in CO_2 which is opposite to most other forecasts. The increase in CO_2 emissions that is commonly projected for transport activity is mainly a result from the increase in freight transport. At the urban level we are studying here, freight transport has a much smaller share in overall transport activity hence the decrease of CO_2 emissions presented here.[18]

Base case transit characteristics

Average bus *occupancy rates* for the baseline are based on data from annual reports of MIVB (MIVB, 2004, 2005), and are assumed to apply to the share of De Lijn and TEC in bus transit operation as well. For metro and tram we again use MIVB data to calculate occupancy rates. For heavy rail we only

[17]The most obvious bias introduced here is that we do not take into account the existence of a small number of CNG-powered vehicles in the MIVB bus stock.

[18]CO_2 emissions from passenger transport activity decrease partially as a result of a baseline decrease in fuel efficiency of new private cars as a result of the greenhouse gas policy by the EU-Commission. A detailed discussion of this policy is provided in chapter 4, on which we based the baseline fuel efficiency evolution implemented here.

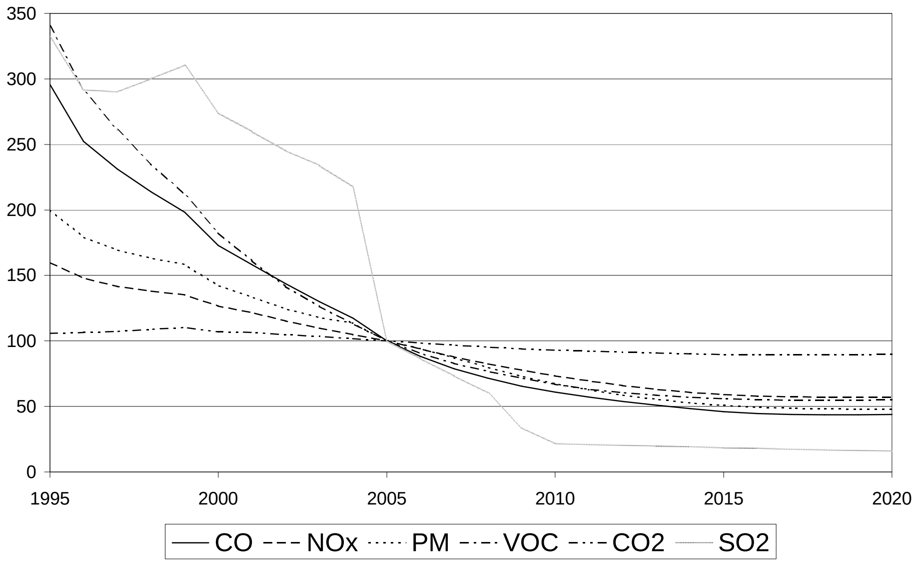


Figure 5.5. Baseline evolution of overall transport emissions (index: 2005 level = 100)

have national average figures and assume that they are also representative for the rail traffic in the Brussels region.

Diversifying the occupancy rates over the time periods (peak and off-peak) is not straightforward. The split over periods of vehicle activity in TREMOVE 2 seems not consistent, resulting in lower occupancy rates in the peak period. We therefore decide to review the TREMOVE 2 baseline on this point. Considering that annual reports by the operators do not provide much information on the peak/off-peak split of the activity (be it pkm or vkm), we make the assumption that peak occupancy rates are twice the off-peak rates. This is a rather rough assumption. We however remark that if we further rise this factor that peak period frequencies become smaller than off-peak, a smaller factor however yields peak occupancy rates which seem to us to be too low to be realistic.

Table 5.3. Baseline frequencies and occupancy rates for the 2002–2004 period

mode	period	occupancy rate			frequencies (per hour)		
		2002	2003	2004	2002	2003	2004
bus	peak	18,82	20,54	25,91	6,16	6,17	6,05
bus	off-peak	9,41	10,27	12,95	4,71	4,73	4,64
rail	peak	100,21	103,42	106,32	8,55	8,65	8,47
rail	off-peak	57,3	59,13	60,78	5,81	5,69	5,63

Occupancy rates before and after the statistical period (2002–2004) are assumed constant in the baseline. We note that for rail the peak occupancy is not exactly a factor two larger than for off-peak. The factor-2 assumption is made at the level of the composing rail modes (tram, metro and train).

Baseline *ticket revenues*[19] are based on annual reports by De Lijn[20], MIVB[21] and NMBS[22]. We assume the average ticket price to be equal over all periods and over the whole network of each operator (both within and out of the Brussels territory), lacking any information on how to diversify this figure. For TEC we assume a revenue per pkm which is identical to De Lijn. Calculating the weighted average we obtain ticket prices (per passenger kilometre) presented in table 5.4. In the same table we also provide an overview of 2004 time cost levels.[23]

We observe that ticket costs are only 10 (rail) to 20% (bus) of total generalised user costs. Waiting costs for rail are higher than for bus although waiting time itself is smaller: this is a result of differences in value of time V_w.

Ticket prices before and after the statistical period (2002–2004) are assumed constant in the baseline. The ticket prices for the composite rail mode in TREMOVE are calculated from constant values for metro, tram and train and aggregated based on the baseline activity of light rail and heavy rail.

Values for the δ and ϵ parameters in the *transit congestion function* are assumed not to change over the modelling period and are presented in table 5.5. The value of the no-travellers speed S for rail is based on the TREMOVE 2 baseline (see section 5.2.1). For buses the value of S is linked to the congestion function of the TREMOVE model. First a value of S is calculated based on observed commercial speed (see section 5.2.1). In a next step the ratio of this no-travellers speed to the network speed value provided by the heavy duty vehicles congestion function of the TREMOVE model is calculated. It is this

[19]The *ticket revenues* are here defined to be equal to all direct ticket related payments collected from the passengers (including season passes). We exclude all other revenues such as subsidies by employers (as far as these subsidies are paid directly to the operator).

[20]Vlaamse Vervoermaatschappij [VVM] (2004, 2005)

[21]MIVB (2004, 2005)

[22]Nationale Maatschappij der Belgische Spoorwegen [NMBS] (2005)

[23]Table 5.4 is limited to cost data based on 2004 observations, cost data for 2002 and 2003 are calculated in an identical way and are only slightly different (or identical for the walking cost).

Table 5.4. Baseline generalised user cost (ticket and time cost) for 2004 (in €/pkm)

mode	period	ticket	walking	waiting	in-vehicle	total
bus	peak	0,090	0,081	0,133	0,173	0,477
rail	peak	0,077	0,371	0,141	0,161	0,750
bus	off-peak	0,090	0,080	0,171	0,153	0,494
rail	off-peak	0,077	0,348	0,197	0,147	0,768

factor (of about 80 to 85%)[24] that we assume constant over the modelling period. A schematic overview of the congestion calibration and simulation is presented in figure 5.6.

Operating costs for buses are determined in the vehicle stock module of the TREMOVE model based on fuel costs, resource costs and driver wage.

Base year fuel prices are based on IEA (2003) and for CNG on Vrije Universiteit Brussel, ETEC (2001). Baseline evolution of fuel prices is based on projections of crude oil and natural gas evolutions based on the PRIMES-transport model Knockaert et al. (2002).

An average fuel consumption of 39 litres per 100 km os assumed for diesel buses in 2000. The specific fuel consumption decreases by 0,6% per year up to 2008 (Verbeiren et al., 2003). Baseline fuel efficiency is further affected by the endogenous fuel efficiency evolution described in chapter 4.

Purchase cost of new vehicles is fixed to €200 000 in 2000 and increases with €15000 between 2005 and 2010 reflecting the implementation of more stringent emissions standards.

Calibration of repair and maintenance cost functions for buses is based on Vrije Universiteit Brussel, ETEC (2001).

The driver wage is assumed constant over the modelling period to 19,8 €/h (see section 5.2.1).

Rail operating costs enter the model exogenously and are assumed constant over the modelling period. Based on the modelled commercial speed value ($1/T$), the model translates per hour costs (wages and capital) to per vehicle kilometre values.

Baseline operating cost values for selected years are provided in table 5.6.

Baseline emission factors for bus vehicles are provided by the COPERT III methodology (Ntziachristos and Samaras, 2000). Buses are assumed to evolve up to Euro 5 standards and to keep this emission levels to the end of the modelling period (2020).

For rail the baseline electricity consumption is aggregated based on data

[24]It seems realistic that the no-travellers commercial speed is somewhat lower than road network average values, considered the near-absence of priority measures for transit as well as the fact that the bus transit network does only make very limited use of the faster urban freeways, as most of them are paralleled with rail transit. The calculated factor does only differ slightly between peak and off-peak (order of magnitude of some percentage points). This observation together with the value of the factor provide an indication that both the values for δ and ϵ as well as the calibration of the TREMOVE congestion curve are realistic.

Table 5.5. Baseline values for parameters of speed-flow relation (in seconds)

	bus	rail
δ	18	0
ϵ	1,8	0,2

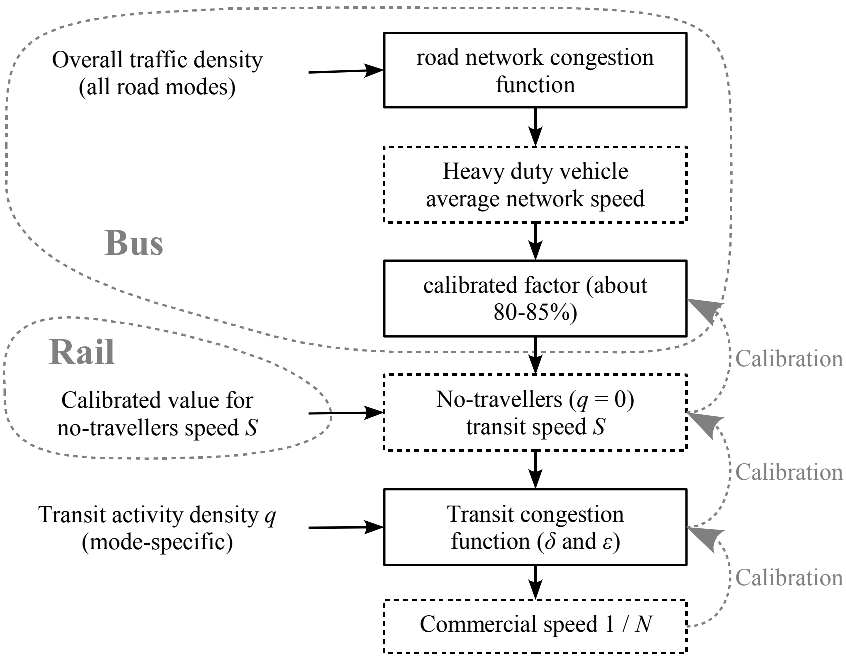


Figure 5.6. Modelling of commercial speed for transit in TREMOVE

Table 5.6. Baseline transit operating costs C_o (in €/vkm)

mode	period	2005	2020
bus	off-peak	1,38	1,39
bus	peak	2,94	3,06
rail	off-peak	6,03	6,00
rail	peak	9,77	9,70

from TREMOVE 2 (G. De Ceuster et al., 2005).

5.4. Policy simulations

In this section we present four policy simulations (see table 5.7). A first simulation focuses on optimising occupancy rates (and through equations (5.2) and (5.3) also frequencies and fleet size) and ticket prices, however without including external emission cost (i.e. $C_e = 0$). This simulation mainly serves to gain insight in first best optimal transit pricing. A second simulation studies how the optimal prices change if we include environmental considerations. A third simulation adds to optimal environmental pricing the midlife retrofit of existing Euro 2 buses in order to meet Euro 5 emission standards. A last simulation studies the environmental and welfare potential of a shift away from conventional diesel technologies to CNG fuelled buses.

All simulations cover the 2006–2020 period, i.e. in the 1995–2005 period the baseline is reproduced.

For completeness we note here that in the simulation where we optimise occupancy rates D we implicitly assume unlimited vehicle capacity. This is not directly an issue as we will see that under all simulations optimal occupancy rates are lower than baseline values. We further note that we assume no change in trip length L_t and network length L_n. Finally we repeat that stop distance d is not optimised and fixed to baseline values.

5.4.1. Scenario 1: Optimal pricing

In a first step we look at optimal pricing of urban bus and rail transit excluding external emission cost ($C_e = 0$).

Using equations (5.5) and (5.10) to determine occupancy rates and monetary user costs for peak and off-peak periods results in a change in generalised user cost presented in figure 5.7. The waiting cost in peak periods does only change a little, indicating that baseline frequencies and occupancy rates are close to optimal levels. In off-peak periods, waiting times reduce significantly as a result of optimal frequencies which are significantly higher than in the base case scenario. The message here is that as a result of peak load pricing the user price in off-peak periods is much lower resulting in a high welfare optimal supply level. Although the optimal frequencies are still lower what is technically feasible with the peak-dimensioned vehicle stock (so part of the fleet is redundant for off-peak operations), the off-peak frequencies for buses

Table 5.7. Definition of the 2006–2020 period in policy simulations

Scenario	Occupancy rates, frequencies, fleet size and ticket prices	Bus technology
Base case	fixed to base case level	Conventional diesel
Scenario 1	welfare optimal excluding external emission cost (equations (5.5) and (5.10) with $C_e = 0$)	Conventional diesel
Scenario 2	welfare optimal including external emission cost (equations (5.5) and (5.10))	Conventional diesel
Scenario 3	welfare optimal including external emission cost (equations (5.5) and (5.10))	Conventional diesel + retrofit Euro 2 $\rightarrow$ Euro 5 in 2006
Scenario 4	welfare optimal including external emission cost (equations (5.5) and (5.10))	CNG for new buses

are above peak levels as a result of the higher commercial speed.

Optimal ticket prices are in all periods much lower than baseline levels. The actual tendency in regional Belgian transport policy (Flanders region) to lower these prices seems in line with the findings of this optimisation.

The important reduction in generalised user cost results in a corresponding evolution in transport activity depicted in figure 5.8. For all transit modes and periods, occupancy rates go down and hence frequency goes up, which results in vehicle km activity increasing more than passenger km. In the off-peak period an increase of 50 up to 100% in transit supply results in an increase by about 40% of the passenger activity.

Studying the impact on transport activity of other modes (figure 5.9) we observe a decrease in private car activity. Overall passenger transport activity increases by about 1,1%. The change in transport activity has an impact on the vehicle stock size: a reduction of about 12% is resulting for private cars. For buses an increase of the stock size of more than 25% is observed. We recall here that the bus stock is dimensioned to fulfil peak demand (see section 5.2.1), and from figure 5.8 we know that the supply of vehicle km during the peak period increases under optimised occupancy rates and ticket prices.

The impact on overall transport emissions is presented in figure 5.10. The increase in emissions of CH_4 and SO_2 results from increased electricity production for rail transit. The relative impact figures are impressive, but the baseline emission levels of these components are very low. The external

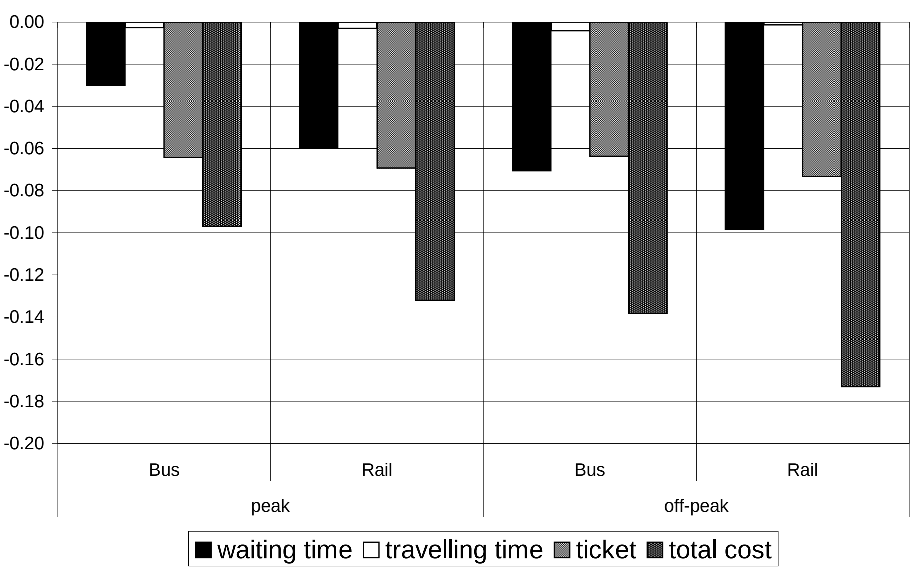


Figure 5.7. Impact of scenario 1 (section 5.4.1) on transit generalised user cost in 2010 (in €/pkm compared to base case (section 5.3.2) levels)

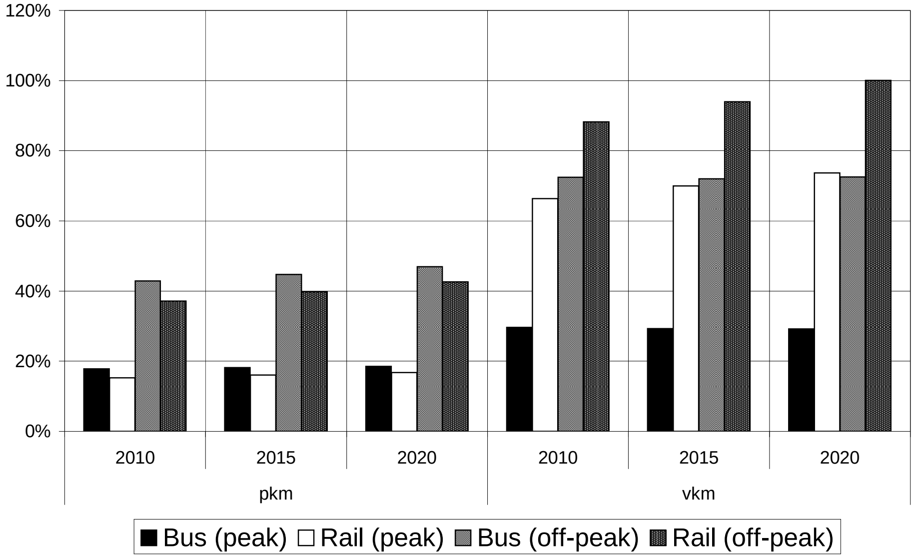


Figure 5.8. Impact of scenario 1 (section 5.4.1) on transit activity (in % change compared to base case (section 5.3.2) levels)

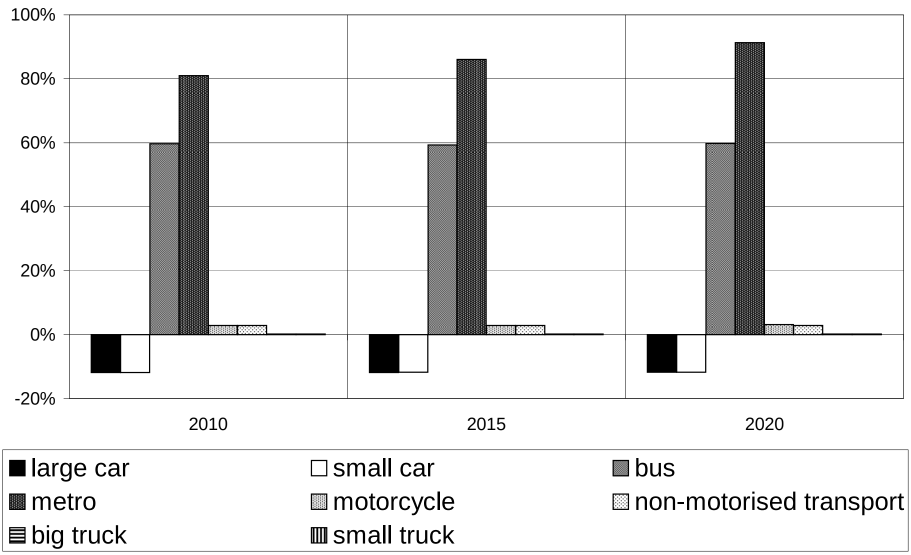


Figure 5.9. Impact of scenario 1 (section 5.4.1) on passenger transport activity (in % change compared to base case (section 5.3.2) vehicle kilometre levels)

cost related to the change in PM emissions is much more important than the change in CH_4 and SO_2 emissions.

The welfare impact of the optimisation of transit markets (bus and rail) may depend on distortions that exist in other markets (see section 5.2.1 and 5.3 on first best versus second best). Figure 5.11 presents the welfare impact. We observe a considerable gain in consumer surplus that is larger than the cost for the government of the change in transit supply. Distortions on the other transport markets do not change this picture significantly: the reduction of private car activity results in a loss in tax income for the government, but the order of magnitude is small compared to the transit supply (and related subsidies) impact on the government budget. The same holds for the MCPF term[25] in the welfare balance.

The impact on external emission cost shows that the increase of transit supply has an environmental cost, however this cost is smaller than the environmental gain resulting from the decrease in private car activity. The net environmental effect is a gain.

Taking all welfare effects together we observe that the welfare optimisation (with $C_e = 0$) of transit generalised user cost results in a net welfare gain.

[25] The MCPF term stands for the *marginal cost of public funds*. It reflects an additional welfare gain if an increase in tax income from transport activity is used to reduce existing distortions in other markets. In this chapter we assume that additional tax income is used for a reduction of labour taxes, the value of the MCPF term used here is 6,6% of the increase in tax income for the government (European Commission et al., 1999).

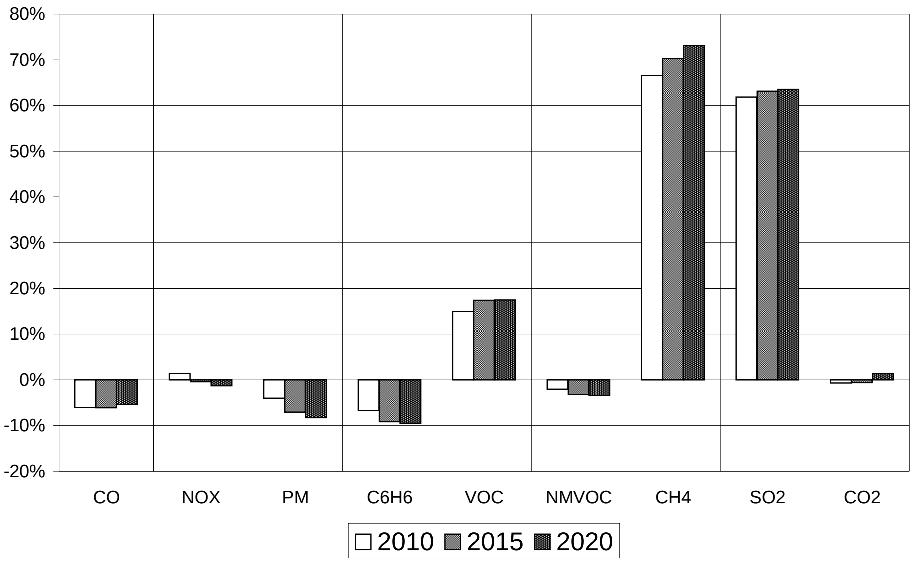


Figure 5.10. Impact of scenario 1 (section 5.4.1) on overall transport emissions (in % change compared to base case (section 5.3.2) levels)

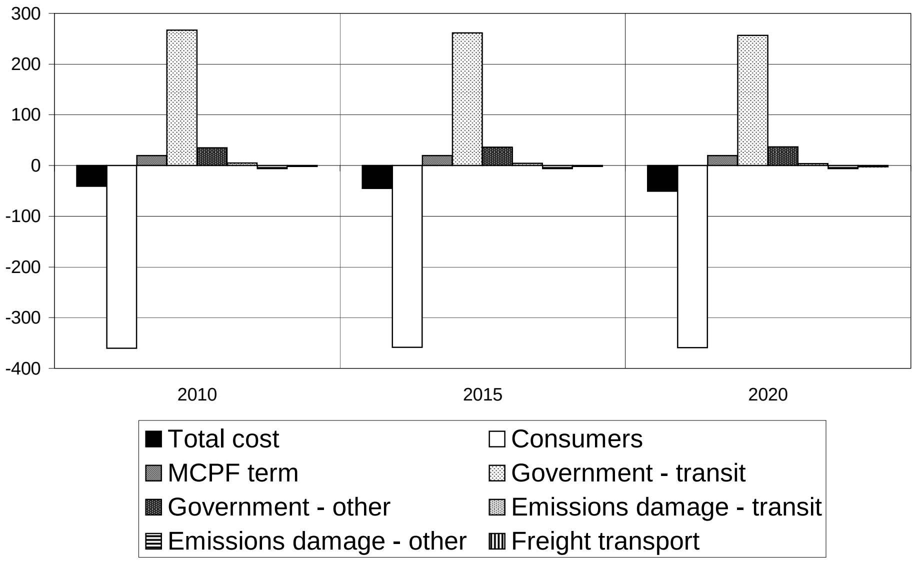


Figure 5.11. Annual welfare cost of scenario 1 (section 5.4.1) in million EUR2000 compared to base case (section 5.3.2)

The 2005 net present social cost of the realisation of this scenario (compared to the baseline) excluding environmental impact is −450 million euro, adding the change in external emission cost this value further goes down to −460 million euro. For clarity we emphasise that a negative cost means a net gain to society.

If we compare our results to findings in past research, we see some obvious parallels. De Borger and Wouters (1998) find optimal prices for public transit that are below baseline levels. On the supply side, vehicle activity levels (in vkm) are to increase much more in off-peak than in peak periods, which is in line with our optimisation results. Also for transit demand (in pkm), both exercises reveal larger increases in off-peak than in peak, be it that these increases are of a much larger magnitude in De Borger and Wouters (1998) compared to our model. This could be explained by the fact that De Borger and Wouters (1998) optimise price levels on the private car market at the same time. The corresponding cost increases for car use likely result in a substantial modal shift towards buses and trams. We should also note that the scope of their exercise covered the whole of Belgium whereas in this chapter we limit our scope to the Brussels region.

The study by Van Dender and Proost (2003) reveals that, for the Brussels area, first best welfare maximisation requires an increase in transit prices combined with a decrease in supply. Their results may be explained by the absence of returns to scale in their model as well as a different road congestion curve applied. Their findings with respect to change in modal shares are broadly in line with our findings, including a strong increase in the share of rail activity but a smaller increase in bus activity.

Based on our simulation we draw the conclusion that welfare optimal frequencies are above baseline levels, especially in the off-peak period when operating costs are lower. We should however remind here that the baseline levels for peak and off-peak frequency are mainly based on an assumption (on occupancy rates) and that only the average frequency (over both periods) is based on actual observations. Conclusions on the exact welfare impact of optimal frequencies may depend on how close we approach real world with our baseline assumption.

Further on we want to remark that the ratio of value of waiting time to value of in-vehicle time has an important impact on optimal frequency levels.[26] As stated before, a broad range of values has been reported in past research for this factor for which we chose the value of 3. Lower values may result in optimal frequencies that are smaller than baseline levels.

Next also operating cost figures have an important impact on optimal frequency levels. Here again we note that the level of the marginal operating cost leaves some space for interpretation as discussed before.

As for the ticket price, we note that the optimal level simulated here is significantly below baseline observations. Changes in value of δ and ϵ have an important impact on this optimal level, however based on some sensitivity analysis we noted that even large increases in these parameters still result in ticket prices which are smaller than or about the same size as baseline levels.

5.4.2. Scenario 2: Optimal pricing and the environment

In the previous section we studied the optimal price level considering the user's own time costs and the transit operator's production cost. In this section we will include external environmental costs related to emissions. The impact figures shown in this section compare the optimal pricing simulations with and without the environmental cost.

First we have a look at the change in transit general user cost (figure 5.12). The increase in user cost is mainly a result of an increase in optimal occupancy rates, resulting in lower frequencies and hence higher waiting costs. For bus, the higher occupancy rate also reduces commercial speed, resulting in an increase in travel time cost. Only a small increase in ticket price is observed. The higher occupancy rates reduce the marginal external emission cost per passenger kilometre by up to 10% for buses and 1% for rail. The increase in total generalised user cost for bus passengers amounts to approximately 60

[26] As can be derived from expression (5.1), it is assumed in calculating average waiting time that passengers arrive at bus or rail stops at a random time without taking into account published timetables. In our setting where intervals are smaller than 13 minutes this seems an acceptable approach.

to 70% of the average emission cost, whereas for rail users the difference is smaller.

The impact on transport activity of the environmentally optimised user costs are presented in figure 5.13. Including environmental considerations mainly impacts off-peak bus supply: a reduction in vehicle kilometre by 12% is observed, resulting in a 2% reduction of transit demand in 2010. Towards the end of the modelling period the impact becomes smaller for bus transit, reflecting the changing composition of the vehicle stock which becomes less polluting as cleaner technologies (Euro 5) enter the stock and replace older, more polluting vehicles (mainly Euro 2).

The change in optimal occupancy rates has an important impact on bus transit supply, the impact on the activity of other modes is much smaller (see figure 5.14). The evolution of overall passenger transport activity is only very small (decrease of less than 0,1%).

Overall emissions from transport activity decrease for most pollutants (figure 5.15). This results in a net reduction in external emission cost (figure 5.16). Note that the decrease in transit environmental cost is larger than the corresponding increase from other modes.

The cost to society of the change in transit generalised user cost is presented in figure 5.16. The loss in consumer surplus is larger than the reduction in government cost for operating the transit network. The gain in tax income from the increase in private car activity together with the MCPF term switches

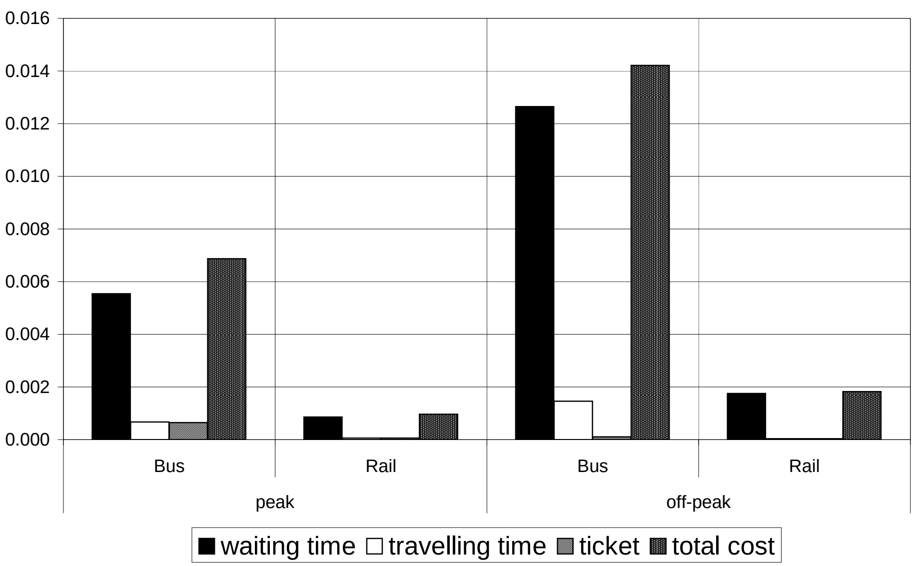


Figure 5.12. Impact of scenario 2 (section 5.4.2) on transit generalised user cost in 2010 (in €/pkm compared to scenario 1 (section 5.4.1) levels)

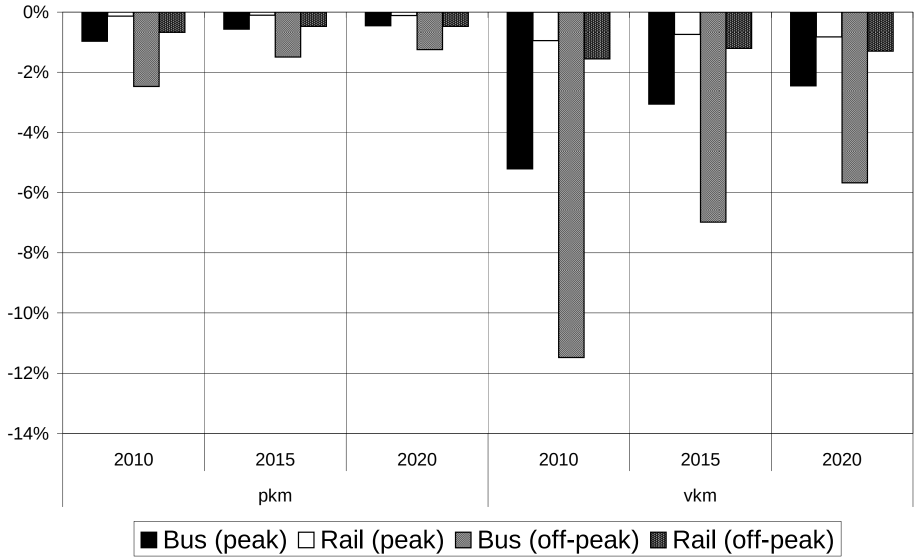


Figure 5.13. Impact of scenario 2 (section 5.4.2) on transit activity (in % change compared to scenario 1 (section 5.4.1) levels)

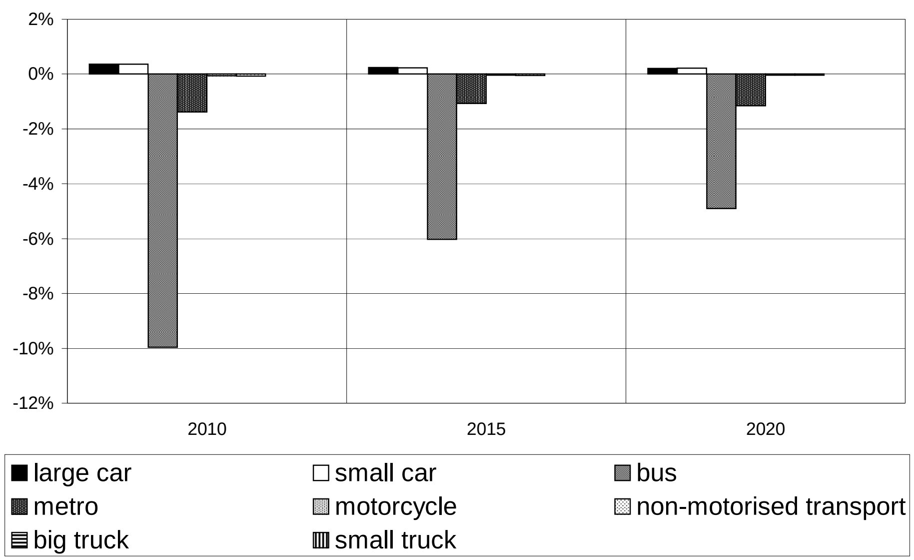


Figure 5.14. Impact of scenario 2 (section 5.4.2) on passenger transport activity (in % change compared to scenario 1 (section 5.4.1) vehicle kilometre levels)

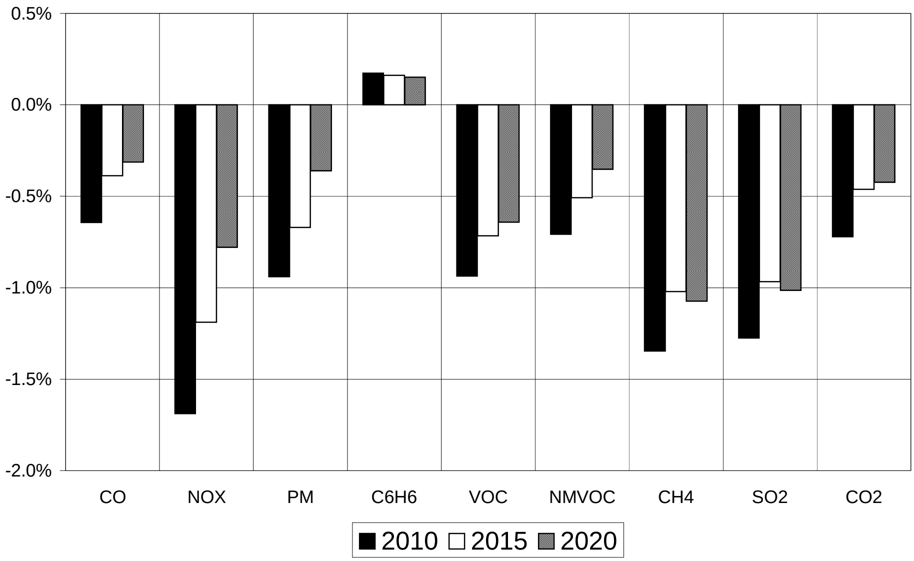


Figure 5.15. Impact of scenario 2 (section 5.4.2) on overall transport emissions (in % change compared to scenario 1 (section 5.4.1) vehicle kilometre levels)

the net result (excluding external emission cost) from a cost to a gain. Distortions in other markets here result in a social gain rather than a social loss. Adding the change in external emission cost further increases the welfare gain.

To conclude, including external environmental costs in the optimisation of transit generalised user cost results in both an environmental and a net welfare gain. By internalising the environmental cost through the waiting time rather than through the ticket price, polluting bus transit supply can be reduced by over 10% with only limited impact on other transport markets.

The 2005 net present welfare cost of the realisation of this scenario (compared to the implementation of scenario 1, section 5.4.1) excluding environmental impact is -14 million euro. Adding the change in external emission cost this value further goes down to -22 million euro. Both welfare and environmental impact over the modelling period show a net gain.

5.4.3. Scenario 3: Retrofitting buses

In this section we study the potential welfare impact of retrofitting Euro 2 buses to meet Euro 5 emission standards. The retrofit is implemented in the model year 2006. In the simulation presented here, this retrofit is added to the optimal environmental transit pricing scenario presented in the previous section. The simulation of the previous section will serve as the reference throughout this section: all changes reported here are relative to environmen-

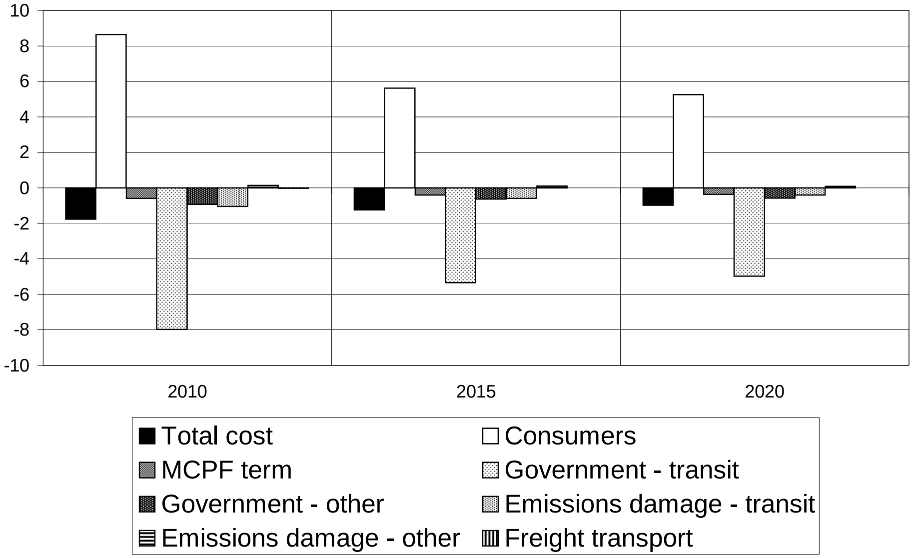


Figure 5.16. Annual welfare cost of scenario 2 (section 5.4.2) in million EUR2000 compared to scenario 1 (section 5.4.1)

tally optimal pricing without retrofit. This allows to fully understand the potential of retrofitting.

Retrofitting part of the existing vehicle stock mainly comes down to reducing its environmental impact. As such, this scenario partially reduces the impact of environmental user pricing. However, the retrofit operation comes at a cost which further impacts optimal pricing. The resulting impact on transit generalised user cost is presented in figure 5.17. Changes in optimal user costs are minimal. Ticket prices increase for both periods reflecting an increase in per vehicle kilometre operating costs. Waiting costs increase in the peak period as a result of peak load pricing of the capital cost to retrofit the vehicles. For the off-peak period, the reduced external emission cost allows to rise frequency and hence reduce waiting and in-vehicle time costs.

The change in transit activity is presented in figure 5.18. The biggest change in supply is noted in the off-peak period where bus vehicle activity increases by some 1,5%. From 2015 on most upgraded Euro 2 vehicles have left the stock hence the small activity impact. The simulation shows only a very small impact on activity of other modes (decrease for private car activity of less than 0,1%).

The impact on overall transport emissions (figure 5.19) is significant compared to the very limited impact on activity of the retrofit implementation. Levels of NO_X and PM decrease by over 1,5%.

The welfare impact of the retrofit operation is presented in figure 5.20.

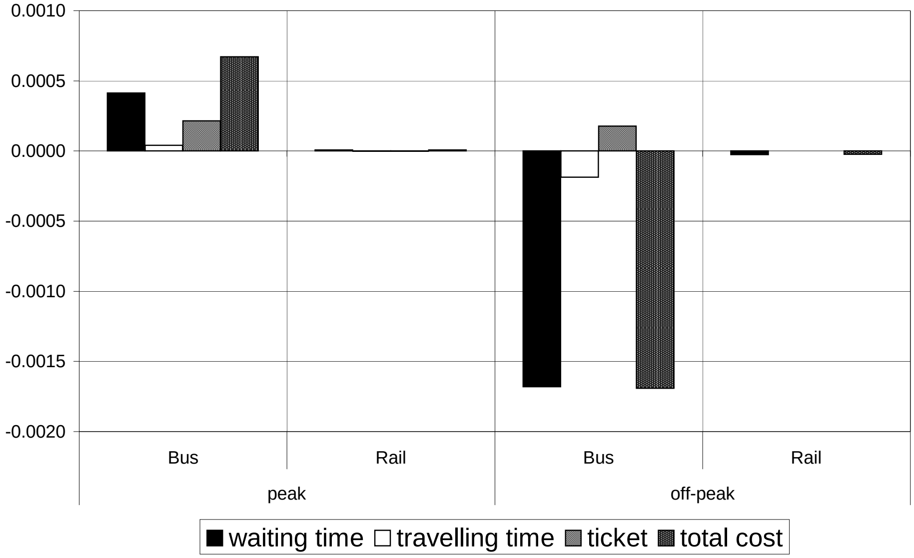


Figure 5.17. Impact of scenario 3 (section 5.4.3) on transit generalised user cost in 2010 (in €/pkm compared to scenario 2 (section 5.4.2) levels)

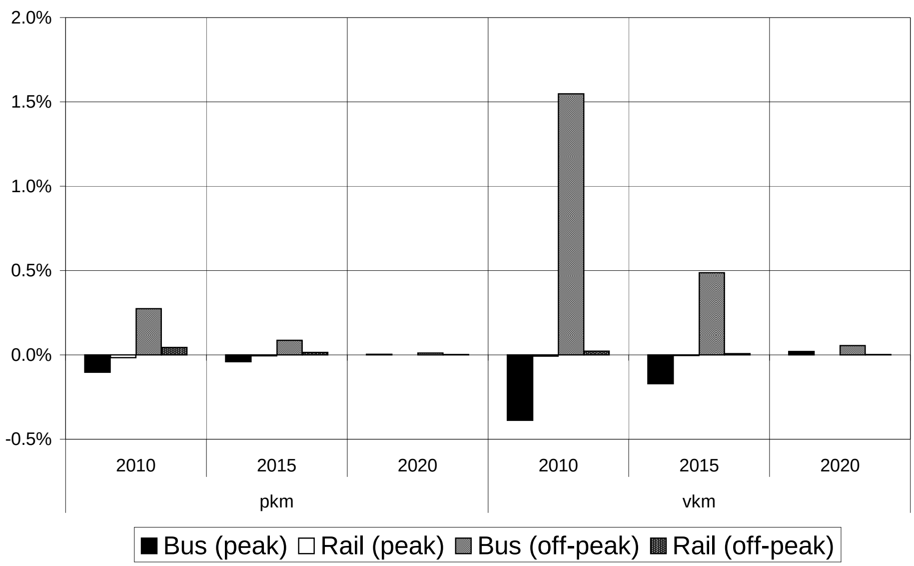


Figure 5.18. Impact of scenario 3 (section 5.4.3) on transit activity (in % change compared to scenario 2 (section 5.4.2) levels)

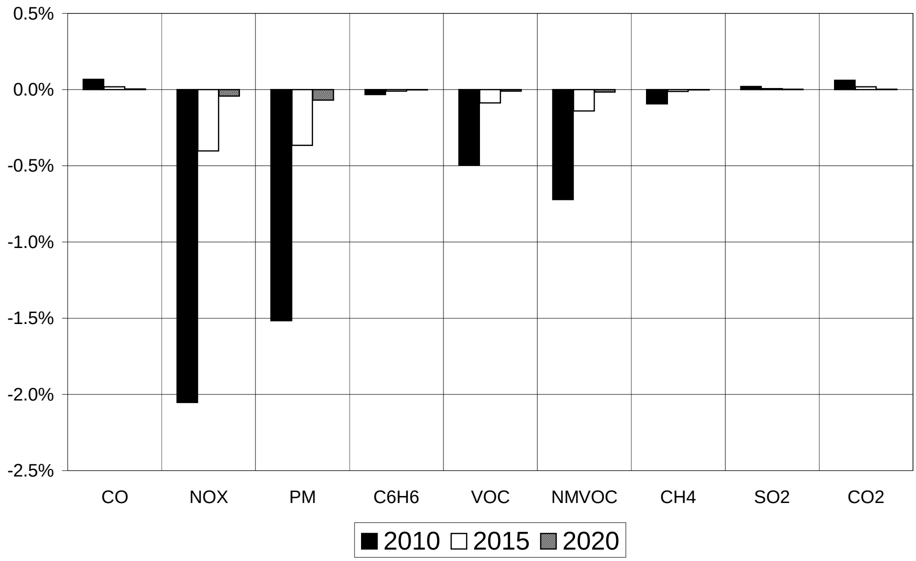


Figure 5.19. Impact of scenario 3 (section 5.4.3) on overall transport emissions (in % change compared to scenario 2 (section 5.4.2) levels)

The higher bus supply in the off-peak period results in a welfare gain for consumers. The gain is smaller than the additional transit operating costs for the government. Adding the external emission cost we however note that the balance is largely positive and results in a net gain in 2010. We again note that the distortions of the other markets do not change the results fundamentally.

The 2005 net present social cost of the realisation of this scenario (compared to the implementation of scenario 2, section 5.4.2) excluding environmental impact is 6 million euro, adding the change in external emission cost this value goes down to −3 million euro. Although the measure results in a cost to society, adding the impact on the environment changes the net welfare impact to a gain.

5.4.4. Scenario 4: CNG buses

In this section we study the introduction of CNG bus technologies. The simulation assumes that from 2006 on all new buses are CNG fuelled. We should remember here that optimising the frequencies and the ticket prices from 2006 on resulted in an increase of the bus stock by over 25% (see discussion of scenario 1 in section 5.4.1). This increase is in this scenario realised by the purchase of CNG buses rather than diesel buses as in the other scenarios. As a result, CNG technology takes up a sizeable share in the stock already in 2006. Beyond 2006, the CNG share further increases at the normal stock turnover rate.

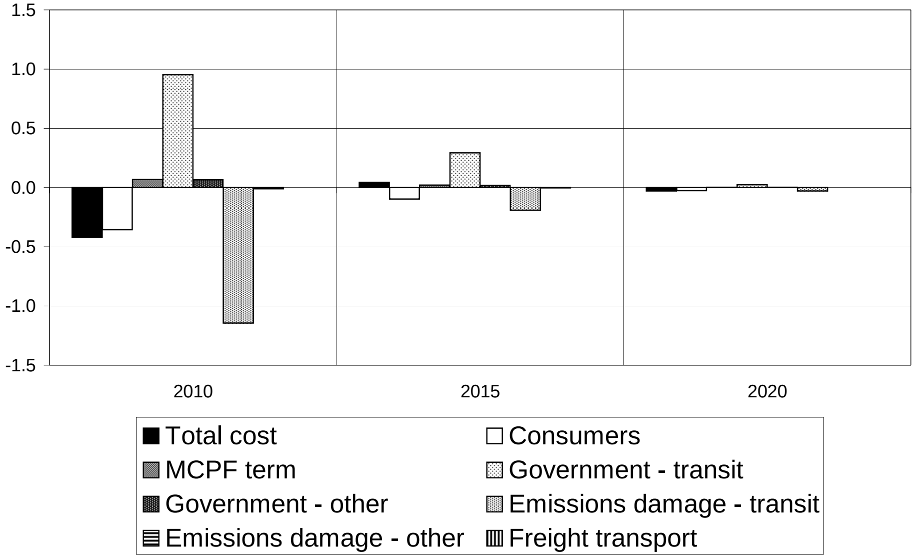


Figure 5.20. Annual welfare cost of scenario 3 (section 5.4.3) in million EUR2000 compared to scenario 2 (section 5.4.2)

We first consider the impact of the CNG vehicles on optimal user cost (figure 5.21). Because of the stock dynamics explained above, we here study the user prices in 2015 rather than 2010. We again note that the main part of the price change comes from a change in waiting cost. Prices go up here, rather than down, an indication that the introduction of CNG technologies has an impact on operating costs that is larger than its impact on external emission cost.

Changes in transit activity are presented in figure 5.22. The impact on passenger transport activity (pkm) is limited. The increased optimal occupancy rate results in a lower vehicle kilometre supply. The change in demand for other modes is very small, private car activity increases by about 0,1%.

The CNG vehicles enter the stock from 2006 on, and by 2020 nearly all diesel vehicles (buses) have been replaced.

The impact of the technology measure on emissions (figure 5.23) indicates a large increase in CH_4 emissions. It is not surprising that CNG vehicles emit more CH_4 than diesel vehicles. The increase is so large mainly because the CH_4 emissions in the reference scenario are so low (mainly from electricity production for rail operation—in which natural gas has a share as primary energy source). As for the external emission cost, the relatively smaller reduction of NO_X and PM emissions will have a much more important impact.

The overall welfare impact of the (mandatory) introduction of CNG bus technology under optimal user prices is presented in figure 5.24. The loss in

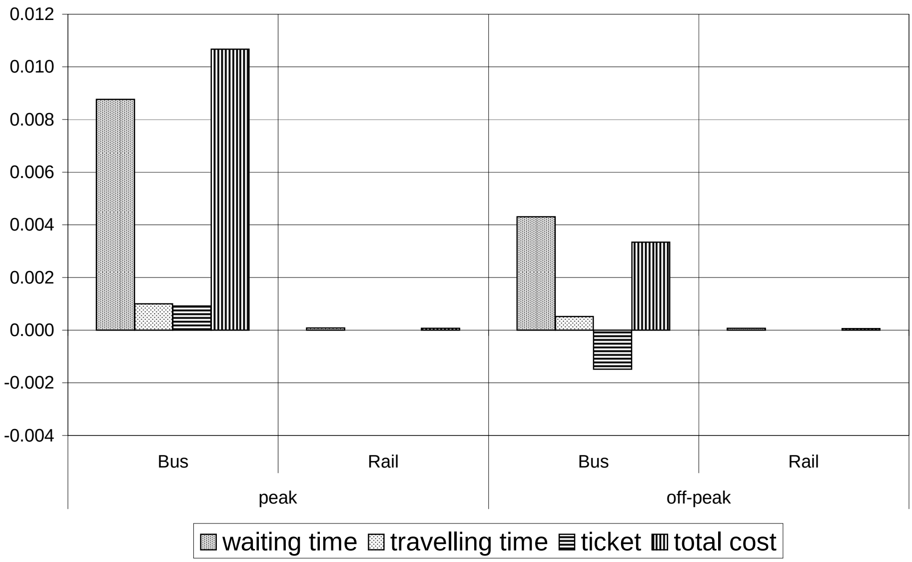


Figure 5.21. Impact of scenario 4 (section 5.4.4) on transit generalised user cost in 2015 (in €/pkm compared to scenario 2 (section 5.4.2) levels)

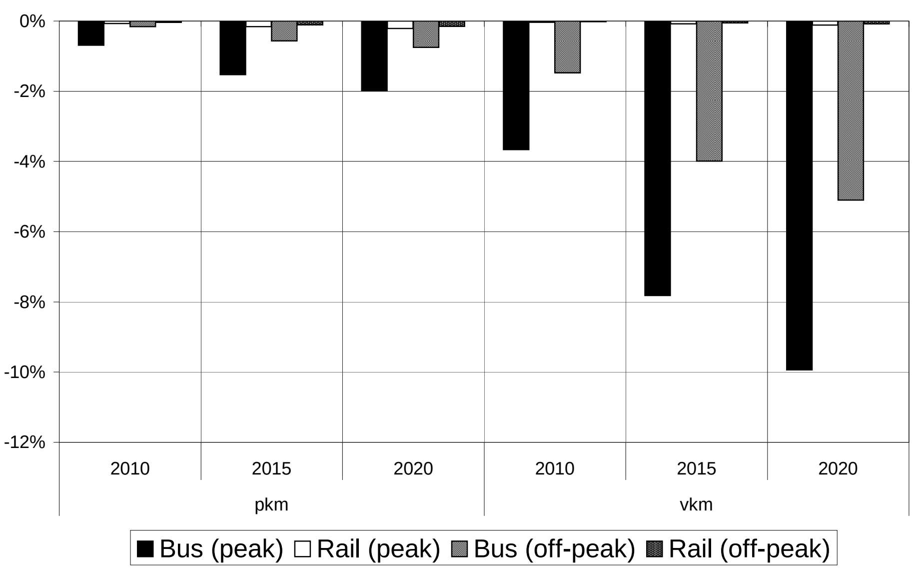


Figure 5.22. Impact of scenario 4 (section 5.4.4) on transit activity (in % change compared to scenario 2 (section 5.4.2) levels)

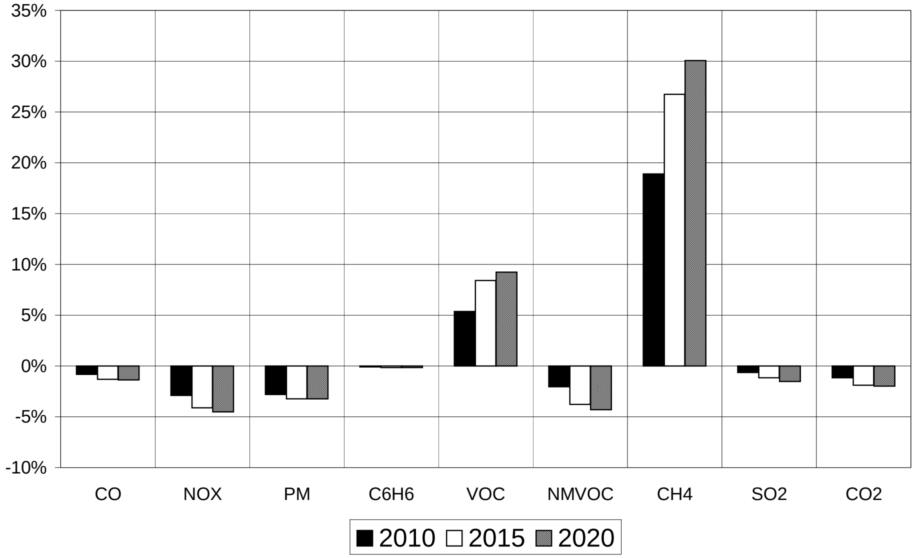


Figure 5.23. Impact of scenario 4 (section 5.4.4) on overall transport emissions (in % change compared to scenario 2 (section 5.4.2) levels)

consumer surplus is approximately as large as the increase in transit operation expenses by the government. The reduction in external emission cost is however of a much smaller order of magnitude, resulting in an overall welfare loss.

The 2005 net present social cost of the realisation of this scenario (compared to the implementation of scenario 2, section 5.4.2) excluding environmental impact is 60 million euro, adding the change in external emission cost this value goes down to 42 million euro. Although the simulation shows a net environmental gain, this gain does not suffice to cover other costs to society, resulting in a net welfare loss over the modelling period.

We draw the conclusion that the environmental impact of CNG buses is rather small compared to the costs incurred for the society.

5.5. Conclusions

In this chapter we studied first best welfare optimal ticket prices and frequencies for urban transit and discussed the environmental potential of technological measures in order to reduce environmental impact of bus transit.

The TREMOVE partial equilibrium model was chosen as a tool to assess environmental and welfare impact of different policy simulations.

Welfare optimal transit frequencies in this simulation are above baseline levels, whereas ticket prices are much lower than under existing transport

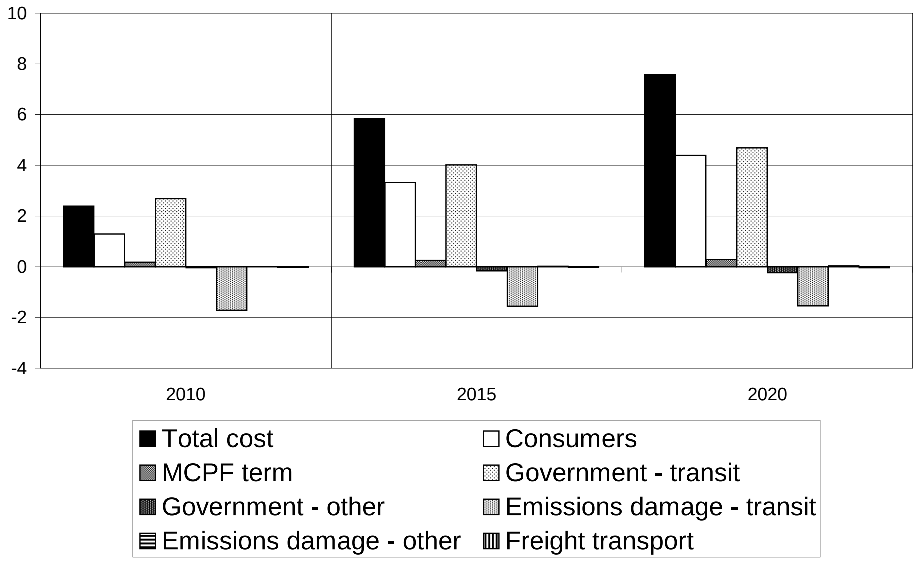


Figure 5.24. Annual welfare cost of scenario 4 (section 5.4.4) in million EUR2000 compared to scenario 2 (section 5.4.2)

policy. This scenario implies a subsidy for transit operations, at a level above the existing situation.

Internalising marginal external emission cost in public transport should be done by reducing frequencies (and hence increasing waiting times) rather than increasing ticket prices in order to maximise welfare. This environmental first best scenario implies a reduction in subsidies for transit operations.

As for technical measures, the retrofit of existing Euro 2 buses to meet Euro 5 standards results in a welfare gain, whereas the switch from diesel to CNG fuelled technology for new bus vehicles does not improve the urban environment sufficiently to cover the increase in resource costs. The simulations show that the welfare gain that comes with technical measures requires an increase in subsidies.

CHAPTER 6

Conclusions

In this chapter we summarise the most important results, and provide an indication of the implications for transport emissions policy.

6.1. Summary of results

The study of modelling road transport emissions is presented in two main parts: the analysis of behaviour of transport users with respect to vehicle technologies, and the simulations of technological and other transport scenarios for emission reduction.

The *analysis* of car buyers' preferences for alternative technologies is based on a focus group and a stated preference experiment to establish a data set for the Flemish car market. The experiment identifies the impact of variables such as user costs, fuel range, trunk space on the choice between conventional and alternative vehicle technologies. No significant preferences for or against hybrid technologies are registered. The survey respondents indicate that they are willing to accept a higher price for cleaner cars, even exceeding net differences in environmental impact. Here and in the focus group it is noted that environmental impact is not consistently assessed by car purchasers using existing indicators as an input.

In the analysis the application of the mixed logit choice model specification plays a central role. It allowed for a model fit that was significantly better than the (nested) multinomial logit by accounting for the repeated choice setting of the experiment. In order to overcome the computational barrier of using mixed logit in simulating transport scenarios where repeated choice is absent, we presented a methodology to design a nested logit simulation model based on mixed logit estimation results. We applied the methodology using the stated preference experiment data set, and demonstrated how the mixed nested logit specification can be used to identify detailed choice correlation in patterns at the level of the respondent.

For the *simulation* of technological and other transport scenarios, we developed a baseline scenario for Belgium using an external transport scenario and reflecting a business as usual setting. The baseline indicates that the existing policy of tightening road transport emission standards for both fuels and new technologies results in a significant reduction in time of environmental impact, both at the level of the individual vehicle and at the aggregate level. Only for CO_2 is there a projected increase at the aggregate level.

In the study of transport scenarios to reduce emissions impact from private car traffic a distinction was made between environmental damage by toxic emissions and external costs of related to climate change by CO_2 emissions. Alternative technologies were found to have a significantly smaller impact on the environment compared to their traditional counterparts. However, in absolute figures the differences are small provided that existing emission standards for traditional technologies are already set tight. Internalising the (small) difference in external emission cost by means of a differentiated charge results in a relatively small gain both for the environment and for society. It was however noted that levelling the playing field between traditional diesel and gasoline technologies allowed to obtain a similar environmental improvement. The environmental contribution of different behavioural adaptations to a pricing scheme evolves in time. In the short term the main contribution stems from overall demand reduction, whereas in the long term with the stock turnover the contribution of technologies increases. Modal shift accounts for 10% or less of environmental improvement.

Reducing CO_2 emissions by private cars is a matter of energy efficiency. The traditional policy approach is one of high fuel taxes combined with (average) emission caps for new vehicles. In our simulations we revealed that it is an example of a policy that is effective but not efficient. Abatement costs per ton of CO_2 emissions are exorbitant compared to other sectors. Even when the policy is limited to an optimal fuel tax setting, the implicated fuel taxes are very high and the net cost for society remains prohibitive. The main rationale is that when a car user substitutes more efficient technology for fuel consumption there is a corresponding substitution of resource costs for (fuel) taxes. This is a net cost to society that by far exceeds the corresponding reduction in climate change impact.

Measures addressing emissions by urban bus public transport depart from the private car scenarios in that the level of service provision provides an additional supply variable which can be tuned for emissions reduction. Here again alternative technologies can contribute to emission reductions, but the relatively long vehicle lifetime compared to other passenger transport modes also makes a case for a mid-life environmental upgrade which proved both effective and efficient. Furthermore it was shown that internalising environmental externalities results in an increase in waiting time rather than ticket price. The 10% decrease in service provision results in an environmental improvement which is not offset by the corresponding shift towards other modes.

6.2. Implications for transport emissions policy

Technological measures to abate road transport emissions generally proved effective in our study. The traditional approach of emission standards for new vehicles resulted in an impressive reduction of emissions from private cars and heavy duty road vehicles, both at the vehicle and at the aggregate level. It is to be expected that a similar approach may prove effective for vehicle types and modes that lag behind in setting emission standards, such as motorcycles, vans, rail and waterways vehicles.

Simulating scenarios where marginal external emission cost is internalised through charges indicates that technology plays an important role in cost effective emission reduction. This provides support for the traditional policy approach of emission standards. For an increase in welfare the technology costs should however not exceed the environmental impact, the latter already being very reduced.

Car buyers' preferences for technologies as captured by the stated choice experiment do suggest that there is a market for alternative technologies without supporting policy measures. There is an environmental improvement related to such an autonomous introduction of alternative technologies.

As for energy efficiency, any improvement of traditional fuels and technologies seems exceedingly cost prohibitive, at least for road modes that face high fuel taxes. A policy approach aiming at reducing CO_2 emissions at minimal social costs (or aiming at maximal reduction for a given social cost) should definitely focus on other sectors before addressing road transport.

Where vehicles have an extended lifetime such as buses or rail, there is a good case for policies that set standards for existing vehicles, especially in urban environments where emissions impact is high.

Pricing measures that aim at supporting an environmentally desirable technological shift in private car transport show us that even with highly differentiated charge the obtainable welfare gains are small. There is however such a thing as a free lunch in this area, where levelling private car diesel and gasoline taxes results in a net environmental and welfare gain. The existing taxation difference is not environmentally motivated.

Encouraging an improvement in energy efficiency of private cars through higher fuel taxes invariably leads to important welfare losses, even if they are 50% smaller than using an efficiency standard for new cars.

Reducing service provision of urban bus public transport can be an effective emissions policy measure. Even when accounting for substitution between modes, such a scenario still has a net environmental and welfare impact.

Across the different scenarios where prices are set equal to marginal social costs we observe that modal shift does not contribute significantly to the reduction of environmental impact. This indicates that policies focusing on a modal shift, even when effective, are probably not desirable from an efficiency point of view.

APPENDIX A

Discrete choice theory

Discrete choice theory provides a broad range of mathematical modelling frameworks. An in depth discussion on discrete choice theory can be found in Ben-Akiva and Lerman (1985), K. Train (1986/1990), Anderson et al. (1992) and K. E. Train (2003).

The introduction on the topic we provide in this appendix is mainly based on K. E. Train (2003) and Heiss (2002).

A.1. Consumer behaviour

The consumer who considers the purchase of a car faces a discrete choice. To model the behaviour in such circumstances, *discrete choice theory* offers several models based on random utility theory.

In these models, the probability that a consumer chooses a given alternative depends on the utility of the alternative as well as the utility of all the other alternatives. This utility U_{jmn} of alternative j as obtained by decision maker n at choice occasion m consists of a deterministic and a stochastic term:

$$U_{jmn} = V_{jmn} + \epsilon_{jmn} \tag{A.1}$$

where:

- V_{jmn}: the *deterministic part* of the utility of alternative j at choice occasion m as obtained by consumer n;
- ϵ_{jmn}: the *stochastic part*.

The deterministic term V_{jmn} can be function both of attributes of the good (alternative j in choice situation m) and characteristics of the consumer n. It is the part of U_{jmn} captured by the researcher.

The stochastic term ϵ_{jmn} accounts for all kind of influences which appear to be random and which make it impossible to observe the choice as a deterministic process. The underlying interpretation is that some characteristics are unobserved or unobservable (for the researcher), and the stochastic term accounts for their influence on U_{jmn}. The probability that the consumer n chooses alternative j in choice situation m is then the probability that the utility U_{jmn} is bigger than the utility of all other alternatives U_{imn} with $i \neq j$ in choice set m (utility maximisation).

Depending on assumptions on the *statistical distribution* of the stochastic term ϵ_{jmn}, different models are distinguished. The *multinomial probit* (with all stochastic terms normally distributed) and the *mixed logit* (with stochastic terms identical and independently Gumbel distributed) specification are the most flexible for discrete choice situations. However, the absence of a closed form for the choice probabilities makes them less flexible for e.g. simulation purposes. The *multinomial* and *nested multinomial logit* specifications do provide for closed form expressions that allow for both fast estimations and simulations, however they allow for less correlation patterns in the stochastic part.

In the next sections we will discuss the multinomial logit, nested logit and mixed logit specifications.

A.2. Multinomial logit

The *multinomial logit* model (MNL) has been applied widely for all kind of logit choice modelling exercises in consumer theory. It is based on the assumption that the stochastic utility terms ϵ_{jmn} (see equation (A.1)) have a double exponential or Gumbel distribution with scale parameter σ ($\mathrm{Var}(\epsilon_{jmn}) = \sigma^2\pi^2/6$) and are independent for all alternatives j, choice situations m and respondents n. The Gumbel distribution shows much similarities to a normal distribution, but its definition allows simplified mathematical manipulation and results in a closed form for the choice probabilities.

The *choice probability* of alternative j from choice set m by consumer n is then:

$$P_{jmn} = \frac{e^{V_{jmn}/\sigma}}{\sum_{i=1}^{J} e^{V_{imn}/\sigma}} \tag{A.2}$$

If V_{jmn} is linear in parameters, the choice probabilities become:

$$P_{jmn} = \frac{e^{\beta' x_{jmn}/\sigma}}{\sum_{i=1}^{J} e^{\beta' x_{imn}/\sigma}} \tag{A.3}$$

with:

- J: the number of alternatives in the choice set[1]
- β: the vector of coefficients
- x_{jmn}: the vector of attribute values of alternative j in choice set m[2]

In formula (A.3) we see that the coefficients β are scaled by $1/\sigma$. Only the product of both can be estimated: β and σ cannot be identified separately. It is common practice to normalise σ to unity, so that it drops out of the formulae. The estimated coefficients $\hat{\beta}$ then indicate the effect of each observed variable relative to the variance of the stochastic utility ϵ_{jmn}. A larger variance in this unobserved preferences leads to smaller coefficients (absolute value). The choice probability of alternative j in the estimated model is then:

$$P_{jmn} = \frac{e^{\hat{\beta}' x_{jmn}}}{\sum_i^J e^{\hat{\beta}' x_{imn}}} \tag{A.4}$$

Although the variance of ϵ_{jmn} cannot be estimated directly, it is possible to calculate the ratio of variances in stochastic utility of two different data sets describing the same choice situation. Take the example of a model estimated on a stated preference (SP) and a revealed preference (RP) data set. The estimated coefficients are $\hat{\beta}^{SP}$ and $\hat{\beta}^{RP}$. We know:

$$\hat{\beta}^{SP} = \beta^{SP}/\sigma^{SP} \tag{A.5}$$

and

$$\hat{\beta}^{RP} = \beta^{RP}/\sigma^{RP} \tag{A.6}$$

The true coefficients (β^{RP} and β^{SP}) should be the same for both RP and SP, as we assume only the variance of the stochastic utility to be different. From (A.5) and (A.6) then follows:

$$\frac{\sigma^{RP}}{\sigma^{SP}} = \frac{\hat{\beta}^{SP}}{\hat{\beta}^{RP}} \tag{A.7}$$

The ratio r of the variance of the stochastic terms ϵ_{nl}^{SP} over ϵ_{nj}^{RP} is then:

$$r = \frac{\left(\sigma^{SP}\right)^2 \pi^2/6}{\left(\sigma^{RP}\right)^2 \pi^2/6} = \left(\frac{\sigma^{SP}}{\sigma^{RP}}\right)^2 = \left(\frac{\hat{\beta}^{RP}}{\hat{\beta}^{SP}}\right)^2 \tag{A.8}$$

The MNL specification has however some important limitations. The stochastic error terms ϵ_{jmn} are supposed to be *independent* (uncorrelated)

[1] We here assume the number of alternatives J to be constant over all choice situations m faced by all respondents n.

[2] The subscript n is added to allow for *interaction variables*, these are technology attributes that interact with respondent specific attributes—it is straightforward from equation (A.3) that respondent attributes that do not interact with alternative variables are constant over all alternatives and hence drop from the formula.

and to have an *identical distribution* (same variance, mean is always zero) for all alternatives j, choice situations m and consumers n. As a result of this, the alternatives have to fulfil the I.I.A. property: *independence from irrelevant alternatives*.

The I.I.A. property can be illustrated by the *red-bus blue-bus problem*. Assume a situation where private cars and red buses have both a 50% market share. That means the ratio of their choice probabilities is 1. Now we introduce blue buses in the system. This does not change the ratio of the share of cars and blue buses (this can be easily verified using formula (A.4)). But we can expect the ratio of the shares of both flavours of buses also to be unity. That means that private cars, red buses and blue buses would all have a 1/3 market share, which is highly implausible. The unrealistic behaviour of the multinomial logit specification results from the independence assumption, which does probably not hold for the error terms of the bus alternatives.

The same phenomenon we described above may happen when choosing between private car technologies. E.g. preferences for diesel and gasoline may be correlated in comparison to electrical cars. This hypothesis is confirmed by e.g. Bunch et al. (1993) and Ramjerdi and Rand (1999) attaining a better fit with a nested model.

In the next section we will discuss a generalisation of the multinomial logit model in order to allow groups of alternatives to be (more) similar to each other in an unobserved way.

A.3. Nested logit

To allow for correlation in preferences for a subset of alternatives, the *nested multinomial logit* model (NL) is applied. A partitioning structure is defined by the researcher by defining subdivisions (nests) in which the alternatives are grouped. For simplicity we will assume a two level structure in the following discussion of the model.

Assume a model with J alternatives partitioned in K nests, denoted $S_1, \ldots,$ S_K. Based on Ben-Akiva and Lerman (1985) we define total utility U_{jmn} (see equation (A.1)) of alternative j in nest k as follows:

$$U_{jmn} = V_{jmn} + \underbrace{\eta_{kmn} + \epsilon_{jmn}}_{\text{stochastic utility}} \tag{A.9}$$

with:

- V_{jmn} the deterministic (observed) utility of alternative j;
- ϵ_{jmn} independent for all alternatives j, choice situations m and respondents n;
- η_{kmn} independent for all nests k, choice situations m and respondents n;
- ϵ_{jmn} iid Gumbel distributed with scale parameter σ_k;

- η_{kmn} distributed so that $\max_{j \in S_k}(U_{jmn})$ is Gumbel distributed with scale parameter σ.

The probability of choosing alternative j is then defined as the product of the marginal probability of choosing (an alternative from) nest k and the conditional probability of choosing alternative j in nest k:

$$P_{jmn} = P_{S_k mn} P_{jmn|S_k} \tag{A.10}$$

Both the *conditional* probability of choosing within a nest and the marginal probability of choosing between nests are multinomial logit. The conditional choice probability of alternative j belonging to nest S_k can be derived directly from (A.9), considering that ϵ_{jmn} is Gumbel distributed and η_{kmn} is constant over alternatives in the same nest S_k:

$$P_{jmn|S_k} = \frac{e^{(V_{jmn}+\eta_{kmn})/\sigma_k}}{\sum_{i \in S_k} e^{(V_{imn}+\eta_{kmn})/\sigma_k}} = \frac{e^{V_{jmn}/\sigma_k}}{\sum_{i \in S_k} e^{V_{imn}/\sigma_k}} \tag{A.11}$$

To define the *marginal* choice probability of nest S_k, we first identify the utility U_{kmn} of nest k in choice situation m by respondent n:

$$U_{kmn} = \max_{j \in S_k}(V_{jmn} + \epsilon_{jmn}) + \eta_{kmn} = \max_{j \in S_k}(U_{jmn}) \tag{A.12}$$

By definition, ϵ_{jmn} is Gumbel distributed. As shown by Domencich and McFadden (1975), $\max_{j \in S_k}(V_{jmn} + \epsilon_{jmn})$ is also Gumbel distributed with scale parameter σ_k, but with expected value:

$$E\left(\max_{j \in S_k}(V_{jmn} + \epsilon_{jmn})\right) = \sigma_k I_{kmn} \tag{A.13}$$

with I_{kmn} the inclusive value of nest k, defined as:

$$I_{kmn} = \ln \sum_{j \in S_k} e^{V_{jmn}/\sigma_k} \tag{A.14}$$

The distribution of η_{kmn} was defined so that U_{kmn} is Gumbel distributed with scale parameter σ. The *marginal* choice probability of nest k is then:

$$P_{S_k mn} = \frac{e^{\sigma_k I_{kmn}/\sigma}}{\sum_{i=1}^{K} e^{\sigma_i I_{imn}/\sigma}} \tag{A.15}$$

We can now write the probability of choosing alternative $j \in S_k$ as:

$$P_{jmn} = P_{S_k mn} P_{jmn|S_k} = \frac{e^{\sigma_k I_{kmn}/\sigma}}{\sum_{i=1}^{K} e^{\sigma_i I_{imn}/\sigma}} \cdot \frac{e^{V_{jmn}/\sigma_k}}{e^{I_{kmn}}} \tag{A.16}$$

We define λ_k as:

$$\lambda_k = \sigma_k/\sigma \tag{A.17}$$

If V_{jmn} is linear in parameters, formula (A.16) becomes:

$$P_{jmn} = \frac{e^{\lambda_k I_{kmn}}}{\sum_{i=1}^{K} e^{\lambda_i I_{imn}}} \frac{e^{\frac{\beta'}{\sigma}\frac{x_{jmn}}{\lambda_k}}}{e^{I_{kmn}}} \tag{A.18}$$

In formula (A.18) we see that the coefficients β are scaled by $1/\sigma$. Only the ratio of both can be estimated: β and σ cannot be identified separately. It is common practice to normalise σ to unity, so that it drops from the formulae. Substituting β/σ for $\hat{\beta}$ gives:

$$P_{jmn} = \frac{e^{\lambda_k I_{kmn}}}{\sum_{i=1}^{K} e^{\lambda_i I_{imn}}} \cdot \frac{e^{\hat{\beta}' x_{jmn}/\lambda_k}}{e^{I_{kmn}}} \tag{A.19}$$

with the *inclusive value* of nest k:

$$I_{kmn} = \ln \sum_{j \in S_k} e^{\hat{\beta}' x_{jmn}/\lambda_k} \tag{A.20}$$

The coefficient λ_k is called the log-sum or inclusive value coefficient of nest k, and is a measure for the correlation (or the degree of dissimilarities) between the alternatives in nest k, with a smaller value for λ_k meaning more correlation.

When λ_k is between zero and one ($\forall k : 0 \leq \lambda_k \leq 1$), the model is consistent with utility maximisation. When λ_k is one, the model becomes a multinomial logit model. For λ_k larger than unity, the model has to be tested for utility maximisation. For negative values of λ_k, the model is not consistent.

Now that we have defined the nested logit specification we should add two considerations in order to avoid any confusion on the topic.

A first consideration relates to the correct specification of the nested logit model. The confusion may arise from the fact that *two different specifications* can be found in literature: the one that we have adopted here and an alternative one where the coefficients that enter the lower model are not divided by λ_k in the expressions for the conditional choice probabilities (expression (A.11)). Heiss (2002) and K. E. Train (2003) point out that only the specification used here is consistent with random utility maximisation (RUM).[3] Software solutions tend to follow literature, resulting in some applying one specification, others implementing the other one while some allow for both. It is unclear to us what may be the use of a non-RUM specification, so we here adopt to use the RUM version. The *nlogit* procedure in Stata implements the non-RUM variant, Heiss (2002) therefore provides the *nlogitrum* command that allows for estimations following the RUM compliant specification. It is the *nlogitrum* procedure that we have used in our estimations in chapters 1 and 2.

[3] Heiss (2002) identifies some restrictions under which the alternative specification is consistent with utility maximisation.

A second consideration relates to the possibility of alternatives that do not belong to a nest. The nested logit framework allows for such a specification, although we did not provide for it in the formulae here to keep them simple. The extension to allow for such alternatives is however trivial.[4]

The nested logit model allows for *correlation in unobserved preferences (or the stochastic part of utility)* at the level of the choice sets m. This is an improvement over the multinomial logit model discussed in section A.2, while not giving up the advantage of having a closed analytical expression for the choice probabilities (A.19), which allows for fast estimation and simulation. However, correlation patterns are limited to the alternatives available in the same choice set. In the next section we will discuss a more flexible extension of the multinomial logit model that allows e.g. for correlation between alternatives j in different choice sets m faced by the same decision maker n (repetitive choices).

A.4. Mixed logit

The *mixed logit* (ML) specification is a further extension to multinomial logit that provides a very flexible modelling framework. The description provided here draws mainly on K. E. Train (2003) and Batley et al. (2003).

Analogous to the multinomial and nested logit models, we will introduce mixed logit by defining the utility U_{jmn} of alternative j in choice situation m by consumer n:[5]

$$U_{jmn} = \alpha' x_{jmn} + \underbrace{\mu_{jmn}{}' z_{jmn} + \epsilon_{jmn}}_{\text{stochastic utility}} \tag{A.21}$$

with:

- α a vector of fixed coefficients
- μ_{jmn} a vector of random terms with mean zero and probability distribution $f(\mu_{jmn})$, any distribution can be used (independence over j, m or n is *not* a necessary condition)
- x_{jmn} and z_{jmn} vectors of observed variables
- ϵ_{jmn} i.i.d. Gumbel distributed with scale parameter σ (independent over all alternatives j, choice situations m and respondents n)

We will again normalise the scale parameter of the Gumbel distributed error term to unity ($\sigma = 1$), this simplifies the notation of the probability of

[4] An alternative approach could be to define single alternative nests. The inclusive value coefficient λ_k of these nests drops from the choice probabilities as can easily be verified from equations (A.19) and (A.20)—in the estimation procedure any arbitrary fixed value will do the job.

[5] We limit here to the case of linearity in variables in order to simplify the notations.

choosing alternative j:

$$P_{jmn} = \int L_{jmn}(\mu) f(\mu) \mathrm{d}\mu \tag{A.22}$$

where $L_{jmn}(\mu)$ is the probability of choosing alternative j in a multinomial logit setting:

$$L_{jmn}(\mu) = \frac{e^{\alpha' x_{jmn} + \mu' z_{jmn}}}{\sum_{i=1}^{J} e^{\alpha' x_{jmn} + \mu' z_{jmn}}} \tag{A.23}$$

Formula (A.22) indicates that the choice probability for a mixed logit is a weighted average of the multinomial logit choice probabilities for different values of μ. The weights are given by density $f(\mu)$. Any arbitrary specification can be used for the distribution $f(\mu)$, normal and log-normal being the most common.

In order to better understand the potential of the mixed logit specification to account for a repeated choice situation, we rewrite the utility formula (A.21) as:

$$U_{jmn} = \alpha' x_{jmn} + \mu_n{}' z_{jmn} + \epsilon_{jmn} \tag{A.24}$$

with μ_n a vector of random terms with mean zero which are independent for all respondents n (but constant over choice sets m).

The error terms μ_n introduce correlation between the utility U_{jmn} of alternatives j of the different choice sets m faced by the same respondent. The vector z_{jmn} may or may not include the same variables as x_{jmn}, this depends on the correlation pattern studied. We will illustrate this by discussing two possible definitions of z_{jmn}.[6]

Specifying $z_{jmn} = x_{jmn}$, equation (A.24) can be rewritten as:

$$U_{jmn} = (\alpha' + \mu_n{}') x_{jmn} + \epsilon_{jmn} \tag{A.25}$$

This specification illustrates how mixed logit accounts for *taste variation* over respondents.

As a second example we specify z_{jmn} to contain one dummy variable δ that has value one for say alternative $j = 1$ and zero for the other alternatives $j = 2 \ldots J$ in choice set m. We rewrite again equation (A.24):

$$U_{jmn} = \alpha' x_{jmn} + \mu_n \delta + \epsilon_{jmn} \tag{A.26}$$

The mixed logit here allows to account for *correlations in the stochastic part of the utility* (which is here $\mu_n \delta + \epsilon_{jmn}$) of alternative $j = 1$ over the choice situations m faced by the same consumer n. This is a clear extension beyond the nested logit specification where correlation was only possible within the same choice set m by consumer n.

[6] Based on the discussion of the mixed logit specification by Batley et al. (2003).

The mixed logit estimation section of chapters 1 and 2 focuses on the correlation in stochastic utility between choice alternatives rather than variation in taste.[7]

[7]For completeness we note that the distinction we make here between *taste variation* and *correlation in the stochastic part of utility* is entirely a difference in interpretation of the error term specification only, as pointed out by Brownstone et al. (2000).

APPENDIX B

Survey choice set

This appendix documents the choice set wording and layout as used in the survey discussed in chapter 1. All respondents received six choice sets. A fictitious example of such a choice set is provided in figure B.1. In this example we assumed the respondent to have indicated that the amount *B* he would spend on a new car would be of 20000 euro.

The example features a random combination of levels for the different variables. It is fictitious in the sense that the combination of the variable levels does not follow the factorial plan used in the survey, and neither have the variables or technology types been randomised. The levels of the variables have been chosen such that almost all labels are shown, the purpose of this example being to document wording and layout of the choice sets.

The fifth technology type (*Voertuig E* in the example) is chosen here to be an electrical battery car. In case the fifth technology type is a fuel cell car, the label for energy is "Brandstofcellen zetten een alternatieve brandstof om in elektrische energie".

The six choice sets sent out to the respondent were preceded by a small glossary, which is provided in figure B.2

Veronderstel dat u nu een nieuwe auto moet kopen. U hebt het model (merk, model, kleur, opties) reeds gekozen. Veronderstel dat er van dit model vijf technische uitvoeringen (motor, brandstof, overbrenging) verkocht worden. Deze zijn voorgesteld in deze tabel en verschillen van elkaar enkel in de eigenschappen die in de tabel staan. Alle eigenschappen die niet in de tabel vermeld zijn, zijn voor alle uitvoeringen gelijk. Dit betekent ook dat alle uitvoeringen even degelijk, veilig, betrouwbaar, en dat de levensduur gelijk is, dat ze hetzelfde vermogen hebben en even snel optrekken.

Eigenschap	Voertuig A	Voertuig B	Voertuig C	Voertuig D	Voertuig E
Motor	Verbrandingsmotor	Verbrandingsmotor	Verbrandingsmotor	Verbrandingsmotor	Elektrische motor
Energie - De opslag van energie is voor alle uitvoeringen even veilig. Het voltanken is voor alle uitvoeringen even eenvoudig en duurt even lang (behalve batterijauto). De brandstof wordt verkocht aan alle tankstations, en de beschikbaarheid is in heel Europa hetzelfde.	Benzine	Diesel	LPG	Alternatieve brandstof	Elektrische energie uit batterijen die worden opgeladen met netstroom. Volledig opladen duurt enkele uren.
Aandrijving	Verbrandingsmotor drijft de wielen aan	Hybride: combinatie van verbrandingsmotor en elektrische motor drijft de wielen aan	Verbrandingsmotor drijft de wielen aan	Hybride: combinatie van verbrandingsmotor en elektrische motor drijft de wielen aan	Elektrische motor drijft de wielen aan
Totale aankoopkost: aankoop voertuig (BTW inbegrepen), inschrijving (B.I.V.), retributie nummerplaat en eventuele kortingen en subsidies.	EUR 17.000 (BEF 685.778)	EUR 20.000 (BEF 806.798)	EUR 23.000 (BEF 927.818)	EUR 20.000 (BEF 806.798)	EUR 20.000 (BEF 806.798)
Totale jaarlijkse kost: verkeersbelasting, verzekering en serviceplan voor onderhoud (BTW inbegrepen), het aantal onderhoudsbeurten is voor alle uitvoeringen gelijk.	EUR 3000 (BEF 121.020)	EUR 3300 (BEF 133.122)	EUR 2700 (BEF 108.918)	EUR 3000 (BEF 121.020)	EUR 3300 (BEF 133.122)
Brandstofkost per kilometer, BTW en accijns inbegrepen, bij een normale rijstijl.	EUR 0,07 per km (BEF 2,85)	EUR 0,05 per km (BEF 2,02)	EUR 0,07 per km (BEF 2,85)	EUR 0,10 per km (BEF 4,03)	EUR 0,07 per km (BEF 2,85)
Bereik: afstand die u kunt rijden met een volle tank zonder bij te tanken (of met volle batterijen zonder bij te laden) bij een normale rijstijl op een vlakke weg.	500 km	500 km	200 km	300 km	500 km
Schadelijkheid uitlaatgassen voor mens en milieu: 100% betekent even schadelijk als gemiddelde nieuwe **benzine**auto die nu op de markt is, 50% betekent de helft minder schadelijk	Even schadelijk als de gemiddelde nieuwe **benzine**auto die nu op de markt is.	Even schadelijk als de gemiddelde nieuwe **diesel**auto die nu op de markt is.	25% van **benzine**auto	100% van **benzine**auto	0%
Beschikbare kofferruimte	100%	100%	30%	100%	30%

Stel dat u moet kiezen uit de vijf voorgestelde uitvoeringen, welke zou u kiezen? U hoeft slechts één keuze aan te geven (geen rangschikking).

Figure B.1. Choice set example

Een woordje uitleg bij de tabel

Eigenschap	Opmerkingen
Motor	**Verbrandingsmotor:** alle auto's die nu verkocht worden zijn uitgerust met dit type motor.
Energie	**Alternatieve brandstof:** een nieuwe brandstof (geen benzine, diesel of LPG). De opslag en het gebruik is voor de verschillende brandstoffen even veilig.
Aandrijving	**Hybride aandrijving:** de verbrandingsmotor en/of een elektrische motor drijven de wielen aan. De elektrische energie wordt geproduceerd door de verbrandingsmotor, en kan (tijdelijk) worden opgeslagen in batterijen (bijv. bij stilstand).
Beschikbare kofferruimte	Voor sommige technische uitvoeringen nemen de installaties extra plaats in waardoor de beschikbare kofferruimte kleiner is.
Schadelijkheid uitlaatgassen voor mens en milieu	Dit zijn enkel de uitlaatgassen van de auto, dus bijv. geen verbrandingsgassen van de productie van elektriciteit om batterijen op te laden. Het percentage geeft aan hoe schadelijk de geproduceerde uitlaatgassen zijn voor mens en milieu.
Serviceplan voor onderhoud	Voor een vast jaarlijks bedrag wordt uw wagen onderhouden. Hierin is ook de vervanging van batterijen inbegrepen.

Figure B.2. Glossary accompanying the choice sets

APPENDIX C

TREMOVE Belgium: specification and calibration

In this appendix we provide an overview of the TREMOVE modelling framework applied throughout chapters 3, 4 and 5 and its calibration for Belgium. The specification of the model as described here is partially based on Van Herbruggen and Logghe (2005).

The model as described here is the starting point for the different modelling extensions discussed in chapters 3, 4 and 5.

C.1. Introduction

C.1.1. TREMOVE 1.3

The TREMOVE 1.3 model is a partial equilibrium representation of the transport markets developed for the EU Commission under the Auto-Oil II Program (European Commission et al., 1999). The model (see figure C.1) represents all the transport markets (passenger and freight), all modes (4 types of cars, metro, public bus, rail etc.) and contains a crude representation of congestion and a detailed emissions module (TRE-part). The model tracks the evolution of the car stock per vehicle type (MOVE stock-part). The model computes the effects and welfare costs of alternative measures to reduce emissions in the transport sector. These measures include taxation and regulation packages ranging from subsidies to public transport and electronic road pricing to the obligation of installing catalytic converters.

The model version for Auto-Oil II covered the 1990–2020 period for 9 EU countries (not including Belgium). Existing transport flow forecast data are used to calibrate the model for every year. For a more in-depth discussion of the TREMOVE 1.3 model we refer to European Commission et al. (1999).

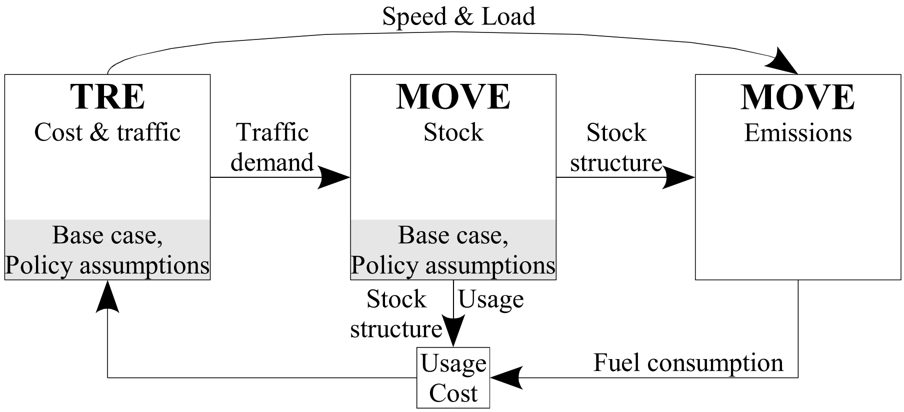


Figure C.1. Structure of the TREMOVE 1.3 model

C.1.2. TREMOVE 2

A major upgrade of the TREMOVE model was conducted in the context of the Clean Air for Europe Programme, which eventually resulted in version 2.30 of the model (commonly referred to as *TREMOVE 2*). The new model covers 21 countries and 8 sea regions. All relevant transport modes are modelled, including air and long-distance maritime transport. The model covers the 1995–2020 period. Full model documentation is provided by G. De Ceuster et al. (2005).

C.1.3. TREMOVE Belgium

The implementation of the TREMOVE modelling framework in chapter 3 was carried out in the context of the Susatrans project (funded by Belgian Science Policy). The timing of this project did not allow to use the final TREMOVE 2 model as a base, so we decided to start from the older TREMOVE 1.3 framework and where possible and relevant for this study to upgrade it.

The geographical scope in chapter 3 and 4 is Belgium, a country that was not included in the TREMOVE 1.3 model. It was hence necessary to collect a calibration and base year data set.

For both the upgrade of the model and the construction of a data set for Belgium we used where possible (draft) results that were timely available from the TREMOVE 2 upgrade.

As discussed in the chapters 3, 4 and 5 the TREMOVE modelling framework was further extended to include the choice for alternative technologies.

The resulting TREMOVE model for Belgium applied in chapter 3 and 4 could be situated as somewhere in between TREMOVE 1.3 and TREMOVE 2, extended with some unique modelling features to allow the simulation of the choice for alternative technologies and an emission tax and enhanced fuel efficiency.

The TREMOVE model for Brussels implemented in chapter 5 is based on the metropolitan area of TREMOVE Belgium as implemented in chapter 4, extended with a more refined representation of public transit including revisited baseline calibration.

In the subsequent sections of this appendix we discuss the TREMOVE Belgium model as implemented for this study.

C.2. TRE: Transport activity demand and supply

The TREMOVE model consists of separate country models that describe transport flows and emissions in three model regions: one metropolitan area, a second region that represents all the other urban areas and a third region for the non-urban areas in the country. Trips in urban areas are further separated in commuter and inhabitant trips. The model explicitly takes into account that, depending on the area taken into consideration, the relevant modes and road types differ significantly. Thus, while the numeric values of the model differ from country to country, the structure is identical across countries.

The transport demand module represents, for a given year and transport mode, the number of passenger kilometres (pkm), ton-kilometres (tkm) and vehicle-kilometres (vkm) that will be realised in each model region. The model differentiates demand over peak and off-peak periods. The demand module allows for the assessment of the impact of policy measures on the demand for the different transport markets.

It may be useful to state here explicitly that TREMOVE models transport activity for each area without a disaggregated transport network representation. This simplification allows for the calibration of a simple but complete policy simulation model using an external baseline of transport demand (which can be based on the output of a more detailed network model).

C.2.1. Methodology

Passenger transport and freight transport are modelled separately in the transport demand module (TRE).

Demand side

The demand for passenger transport is the result of the decision processes of all individuals in a country. Therefore, passenger transport demand has been determined assuming that, with the constraints of their available budget, individuals choose their preferred consumption bundle. Their demand for goods and services follows then from this utility maximising behaviour.

The decision processes of individuals are modelled using nested constant elasticity of substitution (CES) utility functions as described by Keller (1976). Figure C.2 provides an illustration of this nested structure. Based on the consumed quantities and current prices of all different options, a utility value is calibrated. This represents the preference relation of all individuals for the different transport options. The elasticities of substitution are provided exogenously (based on literature) and allow to model the change in demand in policy simulations.

The demand for freight transport is modelled as a result of the decision processes within firms. The freight transport demand is determined by generalised prices, desired production quantities and substitution possibilities with other production factors.

It is assumed that, in any given year, the production level of all firms in a country is given and kept constant. For a given production level, profit maximisation is equivalent with cost minimisation. The cost-minimising substitution process is represented by a nested CES production function. At the highest level, there is the total production, which is a function of the components at the lower levels. At the lowest level, the arguments are the inputs in the production process.

The CES utility and production functions represent demand for transport activity for each transport option (or production input) expressed in passenger kilometre (pkm) or ton kilometre (tkm). This is translated to vehicle activity (expressed in vkm) using a constant transport option specific occupancy rate (or load factor for freight transport) which is calibrated using the externally provided baseline.

Transport modes for passenger trips comprise small car, large car, mo-

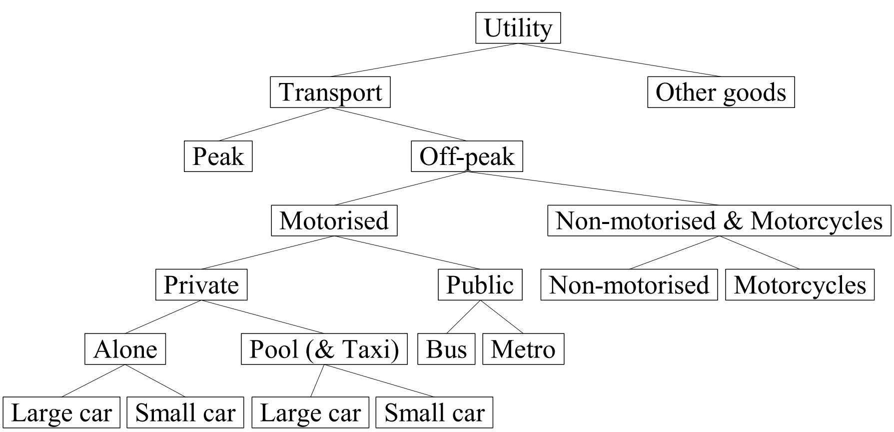


Figure C.2. CES utility function structure for off-peak urban passenger transport in TREMOVE 1.3

torised two-wheeler, non-motorised, bus and rail. Freight trips are realised by light duty vehicles (LDV), heavy duty vehicles (HDV), inland waterways or rail. In non-urban areas two road types are distinguished.

Supply side

The generalised price is the main driver of the transport demand model. This composite cost variable falls apart in roughly three components: resource costs, taxes and time costs.

The resource price for transport services consists of the monetary producer price of all inputs necessary for these services: vehicle purchase, fuel consumption, repair and maintenance etc. The resource costs are calculated in detail in the vehicle stock module (see section C.3) for road modes. For non-road modes, the resource cost values are fixed exogenously. For public transport the peak load pricing principle is applied, attributing all fixed resource costs to peak demand.

On top of the resource costs, the consumer usually pays taxes or receives a subsidy. For road modes this is again calculated in the vehicle stock module, for non-road modes taxes or subsidies enter the model exogenously.

The strict distinction made between resource costs and taxes is important for the assessment of the social cost in the welfare module (see section C.5). In the demand module however, it is the sum of both that determines the user cost.

Time costs are the third component of the generalised price. Time costs depend on the value of time (VOT) and the travel speed. The speed is modelled explicitly for road modes and varies with transport demand, time period and road type. The resulting travel speed values are also used in the emissions module (see section C.4).

C.2.2. Calibration for Belgium

The calibration of the demand module for our model is mainly based on a draft version of the TREMOVE 2 baseline, which is in turn based on an updated version of the SCENES model[1] and the assumption of a constant growth rate.

The evolution in the 1995–2001 period (up to 2002 for railways) has been brought in line with statistical observations as published in the DGTREN Pocketbook (DG TREN, 2004). For the evolution beyond the statistical period the TREMOVE 2 constant growth rate has been applied. We verified this constant growth rate assumption and decided not to reject it.[2]

[1] A specification of the SCENES model is provided in Marcial Echenique & Partners Ltd (2000)

[2] The evolution in TREMOVE 2 is based on the SCENES model results for 2020 which take into account the extension of the network capacity (TEN-networks). The question (not answered

Some smaller amendments to the TREMOVE 2 activity figures had to be made in order to fit the TREMOVE 1.3 classification (see figure C.2). This included a split to alone/pool-taxi and the attribution of the full light duty vehicles activity to freight transport.

In the TREMOVE 1.3 model the congestion function has an exponential form (linking traffic flow to travel time). This functional form was originally proposed by O'Mahony and Kirwan (2001). However our experience revealed that there are some difficulties in using this function for simulation when calibrated on a limited data set. Therefore a new functional form for the congestion function was selected:

$$V_{c,p,r,t} = A_{c,r,t} + B_{c,r,t} F_{p,r,t} \tag{C.1}$$

where

- $V_{c,p,r,t}$ is the speed in year t in period p on road type r for vehicle class c
- $F_{p,r,t}$ is the flow (in passenger car units per hour) in period p on road type r
- $A_{c,r,t}$ and $B_{c,r,t}$ are coefficients
- c is the vehicle class: truck/bus or private car/motorcycle
- r is the road type: Brussels, other urban, motorway or other road
- p is the period: peak or off-peak

The coefficients A and B of the congestion function are calibrated using TREMOVE 2 data (from the SCENES model). Speed differences between peak and off-peak are rather small as they concern speed averaged over the whole network, only a small part of it being congested during peak hours. These small differences have been found to be in line with existing observations for UK and Italy, see TREMOVE 2 documentation (G. De Ceuster et al., 2005) for more details.

Average speed of non-road modes has been taken from TREMOVE 2. Public transport walking and waiting times as well as speed for non-motorised transport have been based on TREMOVE 1.3 data. Value-of-time figures have been taken from TREMOVE 2.

Resource costs for non-road modes are not modelled in the TRE-part and are exogenous to the model. The values for these variables have been based on TREMOVE 2.

by SCENES) is if the growth will occur at a constant growth rate over the period 1995–2020. The assumption made here is that the pace of the infrastructure extension is such that the generalised price of transport (taking into account congestion) is increasing at a constant rate over time (which seems to be a reasonable assumption). Together with the constant growth of income and constant price and income elasticities, this results in a constant transport activity growth.

C.3. MOVE: Vehicle stock composition

The demand module produces aggregate transport activity quantities for each mode. The vehicle stock module further disaggregates these into detailed vehicle kilometre (vkm) figures by technology type and age. This requires a detailed representation of the vehicle fleet structures for each road mode. For non-road modes, no stock representation is implemented in the TREMOVE model applied here.

C.3.1. Structure

The MOVE stock module uses the transport activity data from the TRE-part to calculate for each year and for each vehicle technology class (see table C.1) the desired number of vehicles necessary to meet the transport activity demand level. Based on this desired number of vehicles, the stock of the year before and the number of vehicles scrapped, the level of sales of new vehicles is determined. It is at this point that the technology choice model is applied to determine the market shares of the different technologies for each vehicle technology class.

The technology choice models use the levels of the technology variables as input in order to provide technology share data as output. The technology variables can be roughly split in two categories: cost variables and functional variables (e.g. acceleration). A last category of inputs could be related to the consumer (e.g. age), however these variables fall beyond the scope of the TREMOVE model and as such their potential is limited here.

C.3.2. Technology choice

The technology choice model for private cars is discussed in much detail in chapter 2. For the other road modes we used recalibrated choice models from TREMOVE 1.3 and added a simple choice model for buses.

For the *heavy duty road freight vehicles* we decided to fix the shares of the different weight classes to the observed 1995 shares based on TRENDS data

Table C.1. Link between transport activity demand and vehicle technology classes

TRE transport demand	MOVE vehicle technology class
Motorcycles	Motorcycles & mopeds
Small car	Private cars (< 1,4 litre)
Large car	Private cars (> 1,4 litre)
Bus	Buses
Small trucks	LDV
Big trucks	HDV

(Samaras et al., 2002).

The TREMOVE 1.3 model provides a representation of technology choice for *light duty road freight vehicles* and *motorised two-wheelers*. One model represents the choice diesel versus gasoline for light duty vehicles and a second one the choice between different engine sizes for motorcycles. The models are multinomial logit and use one generic variable (the lifetime cost) and dummies:

$$P_j = \frac{e^{\delta_j - \beta_{cat} LFC_j}}{\sum_{i \in cat} e^{\delta_i - \beta_{cat} LFC_i}} \tag{C.2}$$

with:

- *cat* the technology class (LDV or motorcycles)
- LFC_j the lifetime cost of technology j
- δ_j the coefficient of the dummy related to technology j
- β_{cat} the lifetime cost coefficient for *cat*

For the calibration of the choice models we used cost data from the TREMOVE 2 model (G. De Ceuster et al., 2005). As only one observation is available (1995), we can calibrate the dummies for a given value of β_{cat}.

The values of β_{cat} were chosen such as to result in acceptable dummy coefficient values δ_i.[3] (see table C.2 and C.3) The selected values for β_{cat} are higher for LDV where the choice between alternatives is probably limited to engine technology only (diesel or gasoline), compared to motorcycles where different engine sizes are considered. This seems a reasonable setting. The LFC coefficient value for LDV freight vehicles choice is also higher than for the diesel-gasoline choice for private cars (see chapter 2), reflecting more attention to cost factors in the freight transport sector which is in line with earlier observations (Parker, Fletchall, and Pettijohn, 1997).

For *buses* no vehicle stock model was included in the TREMOVE 1.3 framework. As our simulations will focus on the road passenger transport market and hence modal shifts from/to bus transport can be expected, we decided to refine the representation of that market by including a vehicle stock model. We decided to opt for a deliberately high value for β_{bus} of 40, assuming not only high price sensitivity considering competition being probably as tough as in the freight transport sector, but also resulting from the observation that price differences between diesel and CNG technologies are rather small[4] and that nevertheless CNG technologies do not make it to the market in large

[3] Using the TREMOVE 2 data we did the calibration exercise for 17 European countries simultaneously for given values of β_{cat}. This allowed to identify values of β_{cat} for which the order of magnitude of the calibrated country-specific δ_i coefficients do not take extreme values. Such values of β_{cat} were termed *acceptable* in this context.

[4] User cost data from the TREMOVE 2 model were used here. An overview of alternative bus technologies is provided in appendix D.

quantities.[5] The limitation of the choice model to one explanatory variable (lifetime cost) seems not problematic considering that Parker et al. (1997) indicates that in the trucking sector the choice for alternative technologies is based on user cost only, it seems to be an acceptable assumption that this also holds for the bus transport sector. The bus vehicle stock turnover parameters are based on TREMOVE 2.

C.3.3. Baseline for Belgium

The logit choice models for private cars are based on chapter 2. For the other modes the existing approach of TREMOVE 1.3 was preserved, be it that coefficients were updated making use of data available from the TREMOVE 2 upgrade project. A simple technology choice model for buses was implemented (not available in TREMOVE 1.3). For a discussion of this choice models we refer to section C.3.2.

The baseline of the technical characteristics for conventional technologies is mainly based on TREMOVE 2 data. Alternative technologies are discussed in appendix D.

To initialise the stock module of TREMOVE, base year stock composition data had to be collected. The base year selected is 1995. Stock composition for

[5]Using a lower value for β_{bus} typically results in a substantial market share for CNG vehicles, a result which is not in line with the observation that actual CNG share in new bus sales is zero in Belgium.

Table C.2. Lifetime cost coefficient β_{cat}

category *cat*	value β_{cat}
motorised two-wheelers	5
light duty freight (<3,5 ton gross weight)	25
buses	40

Table C.3. Technology dummy coefficient dum_i

category *cat*	technology *i*	value dum_i
motorised 2-wh.	<50cm^3	0
	50–250cm^3	−0,89
	250–750cm^3	0,76
	>750cm^3	3,31
light duty freight	diesel	0,57
	gasoline	0
buses	*all*	0

this year has been taken from the TREMOVE 2 data, which are mainly based on TRENDS project database (Samaras et al., 2002).

C.4. MOVE: Transport emissions

The emissions module calculates fuel consumption and exhaust and evaporative emissions for all modes. For the TREMOVE Belgium model we used the emissions module developed in the TREMOVE 2 project for road modes. Emission factors for non-road modes were based on different sources.

For road modes, the emissions module implements the COPERT III methodology (Ntziachristos and Samaras, 2000). This approach links emissions to average speed figures that are calculated in the activity demand module. Emission technology types up to Euro 4 (private cars) and Euro 5 (HDV including buses) are represented.

The COPERT III methodology was further extended to include the following additions:

- Disaggregation of the COPERT diesel car fuel consumption factor into three factors according to the engine size. This disaggregation is based on EU CO_2 monitoring data.
- Upward scaling of COPERT fuel consumption factors for 2002 cars, based on EU test cycle monitoring data and information on the difference between test cycle and real-world fuel consumption (R. M. M. Van den Brink and Van Wee, 2001).
- Introduction of fuel efficiency improvement factors. We applied the assumptions by Verbeiren et al. (2003).
- Update of emission factors for motorised two-wheelers based on a more recent study (Ntziachristos, Mamakos, Xanthopoulos, and Iakovou, 2004).

For private cars the emissions module was extended to match the scope of the extended technology choice model presented in chapter 2. The corresponding emission factors are discussed in chapter 3.

For buses the emissions representation was extended to include CNG buses. The emission factors are presented in chapter 5.

For non-road modes we fixed the emission coefficients per vehicle kilometre exogenously. Rail modes are based on TREMOVE 2 baseline data, for inland waterways we implemented the coefficients provided by De Vlieger et al. (2007).

C.5. Welfare module

To evaluate policies in TREMOVE, a welfare assessment module has been developed. Differences in welfare between the baseline (reference scenario) and the simulated policies are calculated.

The utility and production functions of the demand module (see section C.2) are used to calculate a change in consumer (passenger transport) and producer (freight transport) surplus.

Additionally, welfare changes stemming from changes in tax revenues are included by using the marginal cost of public funds. This approach accounts for the options of the government to beneficially use additional tax revenues from the transportation sector to lower taxes in other sectors.

The change in external costs caused by emissions, noise and accidents are assessed and included in the evaluation of the net welfare impact of policy measures. External emissions cost are calculated by applying marginal external cost coefficients (see table C.4) to the emissions calculated by the emissions module (see section C.4).

Table C.4. Marginal external emission cost coefficients C_p in € per ton (source: TREMOVE 2)

Pollutant	Region	1995	2000	2010	2020
CO	Brussels	3,15	3,15	3,15	3,15
	Other Urban	3,15	3,15	3,15	3,15
	Rural	0,83	0,83	0,83	0,83
NO_X	*all*	14000	14000	14000	14000
PM	Brussels	540000	540000	540000	540000
	Other Urban	270000	270000	270000	270000
	Rural	135000	135000	135000	135000
NMVOC	*all*	7100	7100	7100	7100
CH_4	*all*	7284	7284	7376	7560
SO_2	*all*	31000	31000	31000	31000
N_2O	*all*	2368	2368	3552	5920
CO_2	*all*	8	8	12	20

APPENDIX D

Alternative private car and bus technologies

This appendix discusses the baseline evolution of the alternative private car and bus technologies applied in chapter 3 and 5.

Some general remarks:

- all costs are expressed in €2000 and can therefore differ from the original publication;
- some main references used for the baseline evolution: Vrije Universiteit Brussel, ETEC (2001) and Verbeiren et al. (2003).

D.1. Fuels

D.1.1. Ex-tax pomp prices

Ex-tax prices have been based on IEA statistics (IEA, 2003) for the 1995–2002 time span for:

- leaded gasoline
- unleaded gasoline
- diesel for commercial use (including public transport)
- diesel for non-commercial use
- electricity for commercial use (industry tariff) for 1995–2000

Ex-tax prices for other fuels have been taken from different sources for the base years:

- LPG: FEBIAC (n.d.) (1995–2001 with an interpolation for the missing year 1996)

- Natural gas: €0,69 per m^3 in 2001, based on Vrije Universiteit Brussel, ETEC (2001, 37,1 MJ/m^3)
- Electricity for non-commercial use: night tariff of €0,08 per kWh in 2002, based on Vrije Universiteit Brussel, ETEC (2001)
- Hydrogen (from NG): based on Verbeiren et al. (2003) for 2020 and 2010, a linear interpolation has been assumed between these points in time

Production costs for the fossil fuels and electricity have been calculated (for the period 2000–2020) making use of data issued by the PRIMES-transport project (Knockaert et al., 2002). The distribution margin is then calculated as the difference between the production cost and the ex-tax pomp prices:

- unleaded gasoline: €0,084 per litre (2002)
- diesel: €0,052 per litre (2002)
- natural gas: €610,27 per toe (2001)
- LPG: €0,168 per litre (2001)

The evolution of the ex-tax prices beyond the base years (for all fuels) is calculated based on the evolution of the production cost and the margin. The margin is assumed to stay constant up to 2020. From 2009 on we assume an additional cost increase for fossil gasoline and diesel due to desulphurisation (European Directive). This cost increase amounts to 3% for gasoline and 5% for diesel (Verbeiren et al., 2003).

D.1.2. Taxes

VAT

VAT is equal to 20,5% for 1995 and 21% for the years beyond (1996–2020). We do apply VAT only for use by private cars and motorcycles.

Excise taxes

Excise taxes for the period 1995–2002 have been taken from IEA statistics for gasoline and diesel (and domestic electricity up to 2000). Diesel used for public transport is reduced by €0,05 per litre (Vrije Universiteit Brussel, ETEC, 2001).

There are currently no excise taxes on LPG, CNG and electricity (industrial use only). As we assume hydrogen to be based on natural gas, they are freed from excises as well. However, this would imply an indirect subsidy for CNG, electric or hydrogen powered cars when they are introduced. For that reason, we assume an excise tax per unit of energy that is identical to gasoline.

Beyond the base years, excise taxes are kept constant apart from the following exceptions:

- for diesel and gasoline the Cliquet system Federale Overheidsdienst, Kanselarij van de Eerste Minister (2003) has been implemented to determine excise rises for the period 2004–2008

D.2. Private car technologies

D.2.1. Lifetime Cost

The lifetime cost is the expected resource cost per kilometre. It is calculated making use of different variables.

Expected lifetime

For the conventional diesel and gasoline car, the expected (technical) lifetime has been taken from the TREMOVE 2 project: 9,5 years.

For the alternative cars, differences to the reference car have been based on Verbeiren et al. (2003):

- Hydrogen (ICE and hybrid): −2 years in 2010, −1 year in 2020
- Battery: −2 years in 2000, no difference in 2010 and +1 in 2020
- Hydrogen fuel cell: −5 years in 2010, −1 year in 2020

Values have been interpolated between the given points in time.

Fuel efficiency

Base year fuel efficiency of the different engine sizes for conventional gasoline and diesel technologies has been taken from TREMOVE 2, where they have been mainly based on statistics by DG TREN.

An improvement of fuel efficiency of 0,6% per year (1% for the pre-2000 period) has been assumed as reference evolution over time (Verbeiren et al., 2003) from 2000 to 2005. Beyond 2005, no improvement in fuel technology is assumed for all technologies.

The relative fuel efficiency for the alternative technologies has been based on Verbeiren et al. (2003):

- diesel conventional: 5,5 l/100km (2000)
- gasoline conventional: 7,3 l/100km (2000)
- LPG and CNG: according to Verbeiren et al. (2003), these vehicles have the same properties as the conventional gasoline, hence we assume the equivalent energy consumption
- Hydrogen conventional: equivalent energy consumption to conventional gasoline
- Diesel hybrid: 20% more fuel efficient than conventional diesel
- Gasoline hybrid: 5,1 l/100km (2000)

- CNG hybrid: equivalent to gasoline hybrid
- Hydrogen hybrid: 30% less than hydrogen ICE
- Battery: 75 MJ/100km (2000)
- Hydrogen fuel cell: 50% less than gasoline conventional

These relative fuel efficiencies have been applied to the reference evolution of the conventional technologies' fuel efficiency.

Annual mileage

Expected annual mileages have been taken from the TREMOVE 2 project (they are based on TRENDS project data). They are differentiated regarding to engine size:

- engine size <1,4l: 13475 km
- engine size >1,4l: 23020 km

Purchase cost (excl. taxes)

Purchase cost for conventional diesel and gasoline vehicles for the period 1995–2020 are based on TREMOVE 2 data.

The values for 2000 are mainly based on statistics, for the smallest diesel category a review of price differences between diesel and gasoline cars of the same car type available on the market in the first half of 2004 has been used.

For the reference evolution from 1995 to 2020 a price index from the TREMOVE 2 project has been used.

For the alternative technologies, price differences relative to the reference conventional technology has been based Verbeiren et al. (2003, with linear interpolation—see table D.1).

Table D.1. Cost of alternative technologies in €2000 (in addition to cost of reference technology)

Technology	2000	2010	2020	reference technology
LPG	1750	1750	1750	gasoline conventional
CNG	3500	3000	2500	gasoline conventional
Hydrogen conventional		5000	4000	gasoline conventional
Diesel parallel hybrid		5000	3320,2	diesel conventional
Gasoline parallel hybrid	5190	5000	3252,5	gasoline conventional
CNG parallel hybrid		8000	5752,5	gasoline conventional
Hydrogen parallel hybrid		10000	7252,5	gasoline conventional
Battery		1000	1752,5	gasoline conventional
Hydrogen fuel cell		27600	22600	gasoline conventional

Battery leasing costs

For battery electric vehicles we include a leasing cost for the batteries. The leasing cost calculated based on a battery lifetime of 5 years. The battery pack cost is €15000 in 2000 and decreasing to €7500 in 2020.

On battery leasing costs, the normal VAT is levied.

Purchase taxes

These taxes include VAT on purchase as well as registration taxes.

VAT is assumed 20,5% for 1995 and 21% for 1996–2020.

Registration taxes for the year 2000 have been based on TREMOVE 2 data (statistics) for the conventional technologies. For the smallest diesel engine size category (<1,4l) we assumed a tax equal to the smallest gasoline engine size class.

For alternative technologies we assumed the registration taxes to be the same as for the gasoline cars, apart from those technologies running on diesel paying the diesel taxes.

Repair and maintenance costs

Repair and maintenance costs for conventional diesel and gasoline vehicles are calculated making use of the TREMOVE 2 methodology. Inputs for the repair and maintenance costs are purchase price (exclusive VAT and taxes) and expected lifetime, fuel and engine size. For small diesel cars, we assumed the same formula as for small gasoline cars to apply for the calculation of repair and maintenance costs.

For direct injection gasoline cars, we assumed the same methodology as for indirect gasoline.

For diesel hybrid, we assumed the conventional diesel methodology to apply.

For hydrogen ICE we assumed the conventional gasoline methodology to apply to calculate expected repair and maintenance costs.

For LPG and CNG cars, we assumed the same repair and maintenance costs as conventional gasoline based on Vrije Universiteit Brussel, ETEC (2001).

For the hybrid technologies we assumed the repair and maintenance costs to amount to the same level as for their conventional counterparts using the same fuel.

For battery cars, we used Vrije Universiteit Brussel, ETEC (2001) to estimate repair and maintenance costs to amount to 40% of a conventional gasoline car. Here we also add the leasing costs for the battery, which are estimated on €7500 per five years.

For hydrogen fuel cell cars, we estimated repair and maintenance costs to a level of 50% of the gasoline car.

Taxes on repair and maintenance concern VAT only: 20,5% in 1995 and 21% from 1996 onwards.

Annual taxes

Annual taxes for conventional diesel and gasoline vehicles are based on statistical data from the TREMOVE 2 project. For small diesel cars (<1,4l), we assume the annual taxes to be equal to the corresponding amount for the smallest gasoline category increased by a supplemental tax for diesel vehicles of €60,00 per year based on Mira data (M. J. G. De Ceuster, 2003).

For LPG a high additional tax applies (based on Mira):

- LPG <1,4: €120 in addition to the annual tax on gasoline cars of the respective size class
- LPG 1,4–2l: €148,68 in addition to the annual tax on gasoline cars of the respective size class
- LPG >2l: €180 in addition to the annual tax on gasoline cars of the respective size class

The annual taxes for battery cars are considerably lower. For the smallest engine size class we estimate the reduction to amount to €46,33 (compared to the smallest gasoline class, based on Vrije Universiteit Brussel, ETEC (2001)). For the other size categories we assumed a similar relative reduction.

For the other technologies, we assumed the annual taxes to be the same as for gasoline cars (apart from the diesel hybrid, which has the same taxes as the diesel car).

We assume the annual taxes to be constant for the whole modelling period 1995–2020.

Insurance

Insurance costs for conventional diesel and gasoline technologies have been calculated to amount to a percentage of the purchase costs (excl. VAT and taxes), following the methodology used in TREMOVE 2.

For the alternative technologies we assume the same percentages (diesel for diesel hybrid, gasoline for the other technologies) apply to the respective purchase costs to calculate insurance costs.

VAT has been added to insurance cost: 20,5% in 1995 and 21% from 1996 onwards.

D.2.2. Acceleration

Acceleration is used as a proxy for overall driving performance. For the conventional technologies this has been based on statistics. For the alternative technologies this value is taken the same as the conventional reference technology.

Based on statistical data, we assume an improvement in acceleration up to 2005.

D.2.3. Range

A default value for range of 600 km has been taken for all cars.

This variable is primarily included in order to account for discomfort of frequent refuelling due to a range which is significantly reduced by technology design.

According to a report by TNO (Burgwal et al., 2001) we estimate the refuelling range to be reduced for:

- battery cars: ranging from 100 km to 300 km; we assume a value of 100 km in 2000 increasing to 300 km by 2010 and remaining constant afterwards
- fuel cell cars: about 400 km

Additionally, we assume a slightly reduced range of 500 km for hydrogen conventional and hydrogen hybrid and a range of 350 km for LPG and CNG cars (both conventional and hybrid).

D.2.4. Loss of luggage space

The loss of luggage space is used to express a loss induced by technological requirements, e.g. a gas tank.

For LPG and CNG we assume a retrofit installation which causes a loss of trunk space due to installation of a tank:

- LPG: 30 litre (this is the dimension necessary to store the spare tire)
- CNG: 100 litre (this assumption is based on a tank with dimensions 840×316)

For the other alternative technologies we assume dedicated car bodies, hence no loss of luggage space is involved.

D.2.5. Market introduction

Market introduction year of the different technologies is mainly based on Verbeiren et al. (2003) providing an indication on the relative time scale for the introduction of the different technologies:

- gasoline hybrid: 2003
- diesel hybrid: 2008
- natural gas: 2005

- hydrogen ICE: 2010
- CNG hybrid: 2010
- hydrogen hybrid: 2010
- battery: 2005
- fuel cell: 2010

In the TREMOVE model we shift the introduction dates backwards by 3 years to account for full market introduction delay: the dates from Verbeiren et al. (2003) rather indicate the first introduction of the technology. Maybe we need to stress this point a little bit more: TREMOVE assumes full introduction of a technology, which means that is available on all cars bodies, brands, etc. for which the reference conventional technology is available. This also includes the full availability of the fuel.

We also assume an introduction year for the smallest engine size diesel category: 2002.

Conventional diesel, gasoline and LPG technologies have been introduced before the modelling period.

D.3. Buses

For buses we only use the lifetime cost as model variable (see appendix C).

The bus transport activity is linked to both coaches and urban buses. We assume the share of both vehicle types to stay constant.

For the coach vehicle type, we assume only conventional diesel vehicles apply (so no choice model). For the urban bus category, all technology types apply.

The share of coaches is based on the historical 1995 vehicle stock composition (based on TRENDS, see Samaras et al., 2002) and amounts to 20%.

D.3.1. Expected lifetime

The expected (technical) lifetime for a conventional diesel bus has been taken from the TREMOVE 2 project: 20 years (based on TRENDS data).

For the alternative technologies, the difference to the reference has been taken from Verbeiren et al. (2003) (with assumed interpolation):

- hybrid: −5 years (2010); −2 years (2020)
- CNG: −8 years in 2000 and −5 year from 2010 on
- hydrogen fuel cell: −8 years till 2010 and −5 years by 2020
- battery: −8 years in 2000, −5 years in 2010 and −2 years in 2020

D.3.2. Fuel efficiency

An average consumption of 39l for urban buses and 30l for coaches (per 100 km) has been assumed for a conventional diesel bus in 2000.

Assumption regarding the efficiency of other technologies have been based on Verbeiren et al. (2003) (for the year 2000):

- hybrid: 15% better fuel efficiency
- CNG: same energetic fuel efficiency
- hydrogen: 50% better fuel efficiency
- battery: 200 kWh per 100km

An increase in fuel efficiency of 0,6% per year up to 2008 has been assumed, based on Verbeiren et al. (2003). Beyond 2008, no improvement in fuel efficiency is expected.

D.3.3. Annual mileage

The expected annual mileage for buses has been taken from the TRENDS database: 23210 km.

D.3.4. Purchase costs (exclusive taxes)

Purchase costs for all technologies have been based on Verbeiren et al. (2003):

- conventional diesel: €200000 in 2000, a constant reference evolution 2000–2020
- diesel hybrid: an additional cost of 15%
- CNG: an additional cost of 20%
- hydrogen fuel cell: an additional cost €57000[1]
- battery: no additional cost (batteries are leased and hence included in repair and maintenance)

On top of the (constant) reference evolution we add (Verbeiren et al., 2003):

- oxicat, SCR and particulate filter: an increase of €15000 between 2005 and 2010 (€3000 per year), for all diesel driven vehicles

Note that the relative definition of the purchase cost of the alternative technologies implies that they also observe a cost increase in 2010 due to the introduction of oxicat, SCR and particulate filter on conventional diesel buses.

D.3.5. Purchase taxes

No VAT on buses.

Registration taxes have been based on Mira (M. J. G. De Ceuster, 2003) and TREMOVE Vlaanderen (Proost, Meire, and Knockaert, 2004):

[1] Difference to conventional diesel in 2020 has been defined as €42000, so we add the €15000 evolution of the diesel technology to get the reference difference.

- €62 till 2003
- €31 in 2004 and 2005
- €0 from 2006

D.3.6. Repair and maintenance

Expected lifetime repair and maintenance costs for 2001 have been based on Vrije Universiteit Brussel, ETEC (2001). This study assumes an expected lifetime of 10 years:

- conventional diesel: €4637,02
- hybrid: same as conventional diesel
- CNG: €5564,42
- hydrogen fuel cell: €1899,05
- battery: we add leasing costs for batteries (€75000 per five years)

These figures have been adapted in order to account for the different expected lifetime assumption and to allow to apply the TREMOVE methodology (see private cars).

The evolution over time of the repair and maintenance costs is assumed to follow the purchase cost evolution.

No VAT on repair and maintenance costs for buses.

D.3.7. Annual taxes

We assume no annual taxes to apply to urban buses.

For coaches, the annual tax is estimated to €114,46 per year, based on M. J. G. De Ceuster (2003).

D.3.8. Insurance

The insurance cost is estimated to €145,69 per year based on M. J. G. De Ceuster (2003) for all technologies.

No VAT on insurance costs for buses.

D.3.9. Introduction

Introduction years for bus technologies have been mainly based on Verbeiren et al. (2003):

- hybrid: 2010
- CNG: 2000
- hydrogen: 2010
- battery: 2005

Here a similar introduction delay by three years was implemented in TREMOVE.

APPENDIX E

Extended Dutch summary: Economische en technische analyse van uitstoot van wegvervoer

E.1. Inleiding

De bijdrage die het wegvervoer levert aan de economie, en de ermee verbonden maatschappelijke welvaart, is onbetwist. De uitstoot van het wegvervoer brengt echter ongewenste schade toe aan de leefomgeving. De noodzaak om dit negatieve neveneffect te beperken wordt algemeen onderkend door beleidsmakers.

De EU Commissie besteedt in het Witboek Vervoer van 2001 (Commission of the European Communities, 2001) ruime aandacht aan energie-efficiëntie. De Japanse en Amerikaanse autoriteiten voeren een gelijkaardig beleid (Plotkin, 2001). In het Groenboek stedelijke mobiliteitscultuur (Commission of the European Communities, 2007) herbevestigt de Commissie haar streven naar een efficiënt vervoerssysteem dat de leefomgeving respecteert.

Technologische innovatie en beprijzing zijn maatregelen die in de wetenschappelijke literatuur zowel als in de beleidsplannen veel aandacht krijgen. Technologie heeft in de afgelopen decennia reeds bijgedragen tot een substantiele afname van uitstoot zoals erkend door de EU Commissie in haar evaluatie van het Witboek in 2006 (Commission of the European Communities, 2006). Een gedifferentieerd prijsbeleid is daarentegen lang beperkt gebleven tot academische denkoefeningen.

In dit onderzoek bestuderen we de effecten en maatschappelijke kosten van technologische innovaties en ondersteunende maatregelen om uitstoot van van wegvervoer te verminderen. Voor onze analyse ontwerpen we aangepaste modellen voor het simuleren van een reeks vervoersscenario's.

De uitstoot van wegvervoer wordt in belangrijke mate bepaald door de gebruikte combinatie van voertuigtechnologie en brandstof. In ons onderzoek beperken we ons tot effecten van uitlaatgassen en door verdamping vrijgekomen koolwaterstoffen.

Een breed beleidsdomein komt in beeld bij het beperken van uitstoot van wegverkeer. We beperken ons in dit onderzoek tot maatregelen die sturen op een uitstootafname door het wijzigen van eigenschappen van technologieën en vervoerswijzen zoals prijs, beschikbaarheid en brandstofefficiëntie, en die toegepast worden in een groter geografisch gebied. De studie van het innovatieproces alsook de beleidsvorming zelf valt buiten het bestek van dit onderzoek.

Om de *effectiviteit* van een maatregel uit te drukken, volstaat het na te gaan hoe deze de totale uitstoot in het bestudeerde gebied wijzigt. Dit volgt uit het gebruik van technologieën in combinatie met technologie-specifieke uitstootfactoren. We drukken de afname vervolgens uit relatief ten opzichte van een referentiescenario. Dit referentiescenario noemen we de *baseline* en is gebaseerd op een ongewijzigd beleid.

Wanneer twee maatregelen eenzelfde effectiviteit hebben, ontstaat de noodzaak tot een indicator die de maatschappelijk *efficiëntie* uitdrukt. We gebruiken hiervoor de som van alle monetaire en niet-monetaire kosten in het beschouwde gebied. Deze som bestaat uit consumentensurplus, producentensurplus, overheidsinkomsten en externe uitstootkosten. Het optimale maatschappelijke scenario wordt bepaald door een beprijzingsbeleid waarin kosten voor de gebruiker gelijk zijn aan marginale maatschappelijke kosten. Dit scenario noemen we *first-best*.

De uitwerking van uitstootmaatregelen vindt plaats via een wijziging in het gebruik van voertuigen. Elke voertuigtechnologie heeft een specifiek uitstootprofiel en bijgevolg dient nagegaan hoe de bestudeerde maatregel het gebruik van verschillende technologieën beïnvloedt. Op korte termijn kan daarbij de samenstelling van het voertuigbestand als constant beschouwd worden, een wijziging in voertuiggebruik wordt dan veroorzaakt door een afname of toename van de vervoersvraag. Deze wijziging kan verder gedetailleerd worden naar vervoerswijze en de daarmee verbonden voertuigtypes. Op de langere termijn kan een wijziging in vervoersvraag samengaan met een wijziging in de samenstelling van het voertuigbestand. De bestudeerde maatregelen beïnvloeden daarbij voornamelijk de aankoopbeslissing van voertuigen. Aangezien voertuigen na aankoop een langere periode in het bestand aanwezig blijven, duurt het enige tijd voor de samenstelling van het bestand het gewijzigde beleid weerspiegelt.

Factoren die de uitstoot van voertuiggebruik uitdrukken zijn terug te vinden in de literatuur. Traditionele technologieën worden in detail beschreven door Ntziachristos and Samaras (2000), voor alternatieve technologieën zijn meer rudimentaire factoren terug te vinden in Hickman et al. (1999).

De samenstelling van het voertuigbestand wordt bepaald door beslissingen rond aankoop, bezit en sloop van voertuigen. In dit onderzoek zal onze aandacht uitgaan naar het aankoopgedrag dat uitdrukt hoe autokopers kiezen tussen verschillende technologieën. Dergelijk keuzegedrag wordt beschreven door discrete keuzetheorie.[1]

De vervoersvraag voor de verschillende vervoerswijzen wordt bepaald door de gegeneraliseerde prijs in de verschillende bestudeerde vervoersmarkten. Deze is opgebouwd uit voertuigkosten (incl. taksen), brandstofkosten en tijdskosten. De aanbodsfuncties drukken gegeneraliseerde prijs uit als functie van technologische kosten, terwijl de vraagfuncties een gegeneraliseerde prijs relateren aan een vervoersomvang op basis van de voorkeuren van gebruikers. Als functionele specificatie voor de vraagcurves gebruiken we in dit onderzoek het CES model (Keller, 1976).

De toegepaste definitie van maatschappelijke welvaart is gebaseerd op het partieel evenwichtsmodel. Belangrijkste uitgangspunt hierbij is de afwezigheid van verstoringen in niet-bestudeerde markten. Welvaart is dan de som van consumentensurplus (uit CES vraagmodel), producentensurplus (uit CES productiemodel), overheidsinkomsten (met vaste opslag voor de marginale kost van overheidsinkomsten) en externe uitstootkost. Voor deze laatste factor gebruiken we de waardering van de impact van uitstoot gebaseerd op G. De Ceuster et al. (2005) en weergegeven in tabel E.1.[2]

Onze studie van modellering van uitstoot van wegvervoer is opgebouwd uit twee delen. Een eerste deel bestudeert de keuze die autokopers maken voor voertuigtechnologieën, een tweede deel simuleert een reeks vervoersscenario's en analyseert de impact ervan op uitstoot en welvaart.

E.2. Kiezen voor technologieën

De samenstelling van het voertuigbestand en de ermee verbonden uitstoot wordt in belangrijke mate bepaald door de keuze die gebruikers maken bij aankoop van een voertuig. Bij die gelegenheid worden kenmerken van verschillende voertuigen met elkaar vergeleken, en op basis van de eigen voorkeuren maakt de koper de keuze voor een bepaalde technologie.

Voorkeuren voor bestaande voertuigtechnologieën kunnen vastgesteld worden op basis van geobserveerd aankoopgedrag (zie COWI A/S, 2002; De Jong, 1996; Verboven, 1996). Om na te gaan wat het keuzegedrag is voor nieuwe technologieën, en hoe deze voorkeuren afwijken van de keuze voor traditionele technologieën is een andere benadering nodig bij gebrek aan observatiegegevens. Een keuze-experiment waarin autokopers een fictieve

[1] Voor een uitgebreide beschrijving van discrete keuzetheorie zie Anderson et al. (1992); Ben-Akiva and Lerman (1985); K. Train (1986/1990); K. E. Train (2003).

[2] De methodologie voor het waarderen van externe kost van uitstoot is beschreven in Friedrich and Bickel (2001).

Tabel E.1. Marginale externe kost van uitstoot van wegvervoer in € per ton (bron: TREMOVE 2)

Component	Gebied	1995	2000	2010	2020
CO	Brussel	3,15	3,15	3,15	3,15
	Overig stedelijk	3,15	3,15	3,15	3,15
	Niet stedelijk	0,83	0,83	0,83	0,83
NO_X	*alle*	14000	14000	14000	14000
PM	Brussel	540000	540000	540000	540000
	Overig stedelijk	270000	270000	270000	270000
	Niet Stedelijk	135000	135000	135000	135000
NMVOC	*alle*	7100	7100	7100	7100
CH_4	*alle*	7284	7284	7376	7560
SO_2	*alle*	31000	31000	31000	31000
N_2O	*alle*	2368	2368	3552	5920
CO_2	*alle*	8	8	12	20

keuze maken tussen voorgestelde aankoopalternatieven is dan een in de literatuur gebruikelijke benadering (zie Batley et al., 2003; Brownstone and Train, 1999; Bunch et al., 1993; Ewing and Sarigöllü, 1998; Ramjerdi and Rand, 1999).

Het bereik van voertuigtechnologieën dat we bestuderen omvat verbeterde versies van traditionele technologieën (hybride diesel en benzine), alsook technologieën die gebruik maken van alternatieve brandstoffen (bv. aardgas) en nieuwe technologieën (bv. brandstofcellen). De selectie van technologieën is gebaseerd op de technologiescan van Verbeiren et al. (2003).

Op basis van literatuur brengen we in kaart welke eigenschappen van technologieën autogebruikers betrekken in hun aankoopkeuze. Dit wordt verder aangevuld met een focusgroep waarin het aankoopgedrag van autogebruikers kwalitatief in beeld wordt gebracht.

Het keuze-experiment bestaat uit een aantal keuzesets waarin deelnemers telkens moeten kiezen tussen vijf voorgestelde technologieën. De technologieen verschillen enkel in de eigenschappen weergegeven in de keuzesets. Elk keuzeset bevat een dieselauto, een benzineauto, een LPG-auto, een auto op niet-gespecificeerde alternatieve brandstof en een elektrische auto. De voorgestelde technologievariabelen zijn een combinatie van brandstofsoort en aandrijving, aankoopkosten, jaarlijkse onderhoudskosten, brandstofkosten, bereik, uitstoot en kofferruimte. Deze eigenschappen variëren over de keuzesets volgens een orthogonaal factorieel ontwerp dat bestaat uit 72 keuzesets. Elke deelnemer beoordeelt daarvan zes keuzesets.

Het keuze-experiment werd in 2004 uitgevoerd bij een selectie van ruim

200 autogebruikers in Vlaanderen. In een eerste ronde werden deze telefonisch benaderd met het verzoek om deel te nemen. Vervolgens werden de keuzesets postaal toegestuurd samen met een korte toelichting. Tenslotte werden de deelnemers opnieuw telefonisch gecontacteerd om hun keuzes te registreren.

Om de gemaakte keuzes te analyseren gebruiken we discrete keuzetheorie. Daarin wordt aangenomen dat het individu een keuze maakt op basis van het nut U_i van de verschillende alternatieven i. Het nut bestaat daarbij uit een voorspelbaar deel V_i dat bepaald wordt door de (gekende) eigenschappen van het alternatief en de voorkeuren van het individu, en een willekeurig deel ϵ_i dat veroorzaakt wordt door niet geobserveerde eigenschappen en voorkeuren. Het alternatief met het grootste totale nut $\max_i(U_i)$ zal dan gekozen worden:

$$U_i = V_i + \epsilon_i \tag{E.1}$$

Afhankelijk van de (aangenomen) kansverdeling van ϵ_i onderscheiden we een aantal categorieën van keuzemodellen. Het rekenkundig eenvoudigste model is het multinomiale logit model waarin de ϵ_i onafhankelijk Gumbel-verdeeld zijn. Wanneer de niet geobserveerde voorkeuren ϵ_i voor bepaalde alternatieven binnen eenzelfde keuze gecorreleerd zijn, kan gebruik gemaakt worden van een geneste logitspecificatie.

In het uitgevoerde experiment heeft elke deelnemer zes keuzesets beoordeeld, bijgevolg kan verwacht worden dat ϵ_i ook gecorreleerd is over keuzes die gemaakt zijn door dezelfde deelnemer. Een gemengde logit specificatie laat toe om complexere correlatiepatronen te testen.

Voor de bestudeerde modelspecificaties schatten we coëfficiënten van technologie-eigenschappen steeds generiek. Daarnaast voegen we technologie-specifieke dummy-variabelen toe, alsook een beperkte selectie interactie-variabelen waarin we bestuderen of keuzegedrag significant verschilt over subpopulaties (bv. man/vrouw).

Uit de analyse komt naar voor dat bijna alle bestudeerde technologievariabelen een significante invloed hebben op het aankoopgedrag. Enkel de *hybride* eigenschap heeft geen onderscheiden impact ceteris paribus. De correlatie in niet geobserveerde voorkeuren komt overeen met bevindingen uit de literatuur waar voorkeuren voor conventionele technologieën gecorreleerd zijn. Tenslotte bevestigt ons onderzoek eerdere bevindingen waaruit het belang blijkt om rekening te houden met correlaties in voorkeuren over verschillende keuzesets van dezelfde deelnemer.

In tabel E.2 geven we ter illustratie een gemengde logit keuzemodel waarin de coëfficiënten van de diesel en benzine dummy-variabelen variëren over deelnemers volgens een normaalverdeling.

De gemengde logit modellen bieden uitgebreide mogelijkheden om het gedrag uit het keuze-experiment te analyseren en daarbij rekening te houden met te verwachten correlatiepatronen in voorkeuren. Deze modellen hebben echter beperkingen ten aanzien van de benodigde rekentijd. In modelschatting is dit geen bepalende factor, maar voor toepassing in een simulatiemodel wel.

Tabel E.2. Gemengde logit keuzemodel

Variabele	Eenheid	Coëfficiënt	p-waarde
Verwachte coëfficiëntwaarde			
Aankoopkost	1000€	−0,1851	0
Jaarlijkse kost	1000€	−0,8029	0
Brandstofkost	€/km	−15,8720	0
Kofferruimte	0–1	1,1743	0
Uitstoot	0–1	−0,3463	0,211
Bereik	100km	0,3154	0
Diesel		1,0528	0
Benzine		0	vast
LPG		−0,4094	0,156
Alternatieve brandstof		0,4468	0,140
Brandstofcel		0,3411	0,351
Batterij		0,0408	0,911
Hybride		0,0354	0,708
Uitstoot × vrouw		−1,2162	0
(diesel | alternat. brandst.) × man		−0,6917	0,001
Variantie van technologie-voorkeur over respondenten			
Diesel		7,9736	0
Benzine		6,0151	0
Correlatie van technologie-voorkeur voor diesel en benzine			
		0,4262	
Log likelihood		−1440,327	

In de simulaties die we in het volgende deel willen uitvoeren, bestuderen we de aandelen van voertuigtechnologieën op jaarbasis. Er is bijgevolg geen sprake van herhaalde keuze (binnen hetzelfde jaar), waardoor de noodzaak voor het gebruik van gemengde logit vervalt en een geneste logit volstaat voor het simuleren van de (belangrijkste) correlatiepatronen. Daarom bestuderen we hoe we de bevindingen uit de gemengde logit gedragsanalyse kunnen gebruiken in het ontwerp van een geneste logit gedragsmodel.

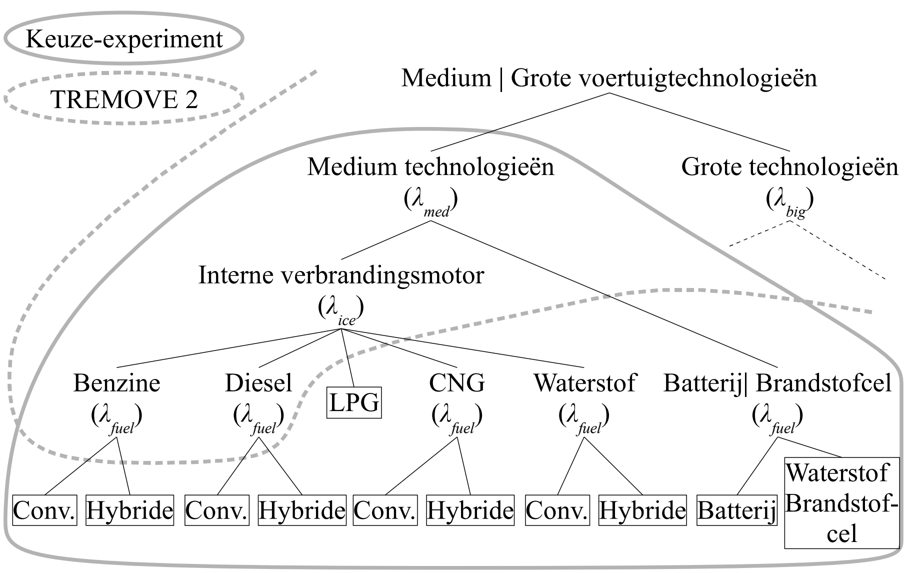
De oplossing bestaat erin om in de gedragsanalyse gebruik te maken van een gemengde geneste logit specificatie (K. E. Train, 2003). In dit onderzoek bestuderen we de methodologie om een genest logit simulatiemodel op te stellen dat de gemengde geneste logit zo goed mogelijk reproduceert in een enkelvoudige keuzesituatie. We tonen verder aan hoe correlaties in voorkeuren over verschillende keuzesets kunnen vertaald worden naar een enkelvoudige keuzesituatie waarin een uitgebreider aantal alternatieven beschikbaar is.

Als voorbereiding op het simuleren van vervoersscenario's in het volgende deel, integreren we tenslotte het keuzemodel voor alternatieve voertuigtechnologieën met het bestaande keuzemodel (voor conventionele technologieen) van het vervoersmodel TREMOVE. Hiervoor gebruiken we de in de literatuur beschreven methode (zie bijvoorbeeld Ben-Akiva and Morikawa, 1997; Brownstone et al., 2000) voor gezamenlijke schatting van keuzemodellen op basis van werkelijke en fictieve keuzes. We tonen hoe deze methode kan toegepast worden in de context van twee geneste logit modellen die slechts een enkele generieke variabele gemeen hebben (levensduur kost die alle kosten over volledige levensduur van het voertuig samenneemt). Het resulterende model is weergegeven in figuur E.1 en tabel E.3.

E.3. Leren uit simuleren

Het tweede deel van het onderzoek richt zich op het bestuderen van effectiviteit en efficiëntie van een reeks vervoersscenario's waarin technologische innovatie wordt toegepast om uitstoot van wegvervoer te doen afnemen. Achtereenvolgens bestuderen we impact op de leefomgeving en klimaatverandering van personenauto's, en impact op de stedelijke leefomgeving van openbaar busvervoer. Voor elke toepassing gebruiken we een aangepaste versies van het TREMOVE simulatiemodel. Dit vervoersmodel levert een consistent referentiekader om verschillende technische en niet-technische maatregelen met elkaar te vergelijken.

De verschillende scenario's bestuderen telkens de gevolgen van een kleine wijziging in externe factoren op de vervoersactiviteit en de daarmee verbonden uitstoot tijdens de beschouwde modelleerperiode. Op die manier kunnen we de individuele impact van geïsoleerde beleidsmaatregelen inschatten.



Figuur E.1. Genest logit simulatiemodel

Tabel E.3. Coëfficiënten van het genest logit simulatiemodel

Variabele	Eenheid	coëfficiënt
levensduur kost/kwartaal BNP	levensduur kost in €/km BNP in 10k €	−0,4585
Kofferruimte	0–1	0,08418
Uitstoot	0–1	−0,06361
Bereik	100 km	0,02220
Acceleratie	s	−0,04557
Diesel		0,1939
LPG		−0,05059
Batterij		−0,04526
Grote technologie		−2,5105
kwartaal GDP × grote technologie	10k €	1,738
λ_{ice}		0,8664
λ_{fuel}		0,5952
λ_{med}		0,1270
λ_{lar}		0,1804

In een gesimuleerd scenario is de tijdsperiode waarover we een of meerdere externe factoren wijzigen volledig arbitrair. Om tot zinvolle inzichten te komen is het echter van belang om rekening te houden met de levensduur van voertuigtechnologieën. Om te begrijpen wat er gebeurt op de langere termijn, is het daarom vereist dat gesimuleerde maatregelen over een voldoende lange periode toegepast worden. Hierbij dient rekening gehouden met de modelleerperiode die eindigt in 2020, in functie van de externe beschikbaarheid van voldoende gedetailleerde en consistente baseline voorspellingen van de vervoersvraag die nodig zijn om het model te kalibreren.

De essentie van de modeltoepassing in dit onderzoek is het consistent vergelijken van individuele ingrepen. In geen geval kunnen modelresultaten beschouwd te worden als toekomstvoorspellingen. Om tot zinvolle voorspellingen van de vervoersvraag te komen dient een zeer uitgebreide verzameling variabelen beschouwd te worden. In TREMOVE daarentegen wordt de baseline evolutie van vervoersactiviteit en prijzen over de modelleerperiode als gegeven beschouwd bij de modelkalibratie, bijgevolg valt elke toekomstvoorspelling buiten het bereik van het model.

Evenmin is TREMOVE geschikt om scenario's te optimaliseren. In een statische context kan het verhelderend zijn om welvaartsoptimale prijszetting te bestuderen in functie van diverse beleidsbeperkingen. Echter maakt het tijdsdynamische karakter van TREMOVE, waarin de evolutie van het voertuigbestand een rol speelt, dergelijke optimalisatie complex en bovendien in belangrijke mate afhankelijk van de toegepaste verdiscontering.

In de simulaties zijn alle waarden uitgedrukt in constante prijzen van het jaar 2000. Waar actualisatie wordt uitgevoerd, wordt uitgegaan van een discontovoet van vier procent per jaar.

De gemeenschappelijke basis voor de simulaties is het TREMOVE model voor België. We passen hier een hybride versie toe die versie 1.3a (European Commission et al., 1999) combineert met uitbreidingen van versie 2 (G. De Ceuster et al., 2005).

E.3.1. De keuze voor schone technologieën

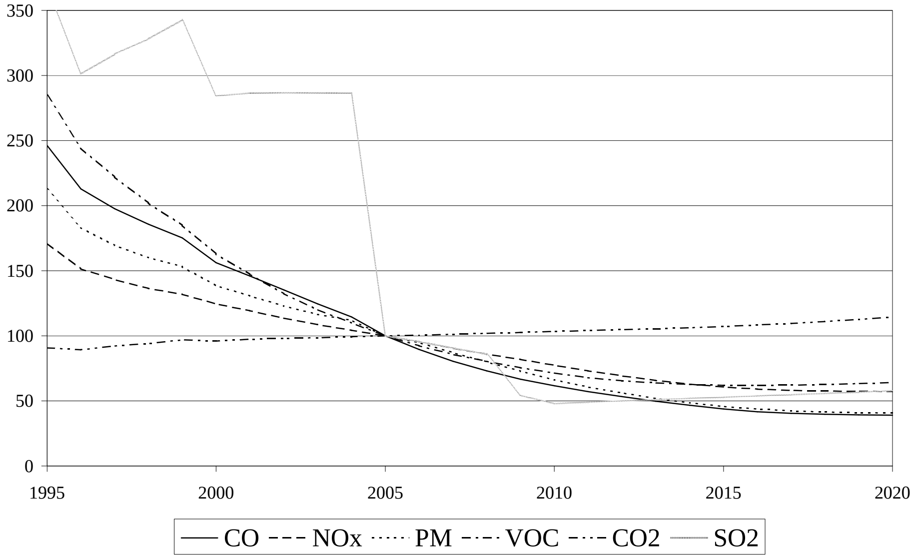
In een eerste reeks simulaties bestuderen we de bijdrage die schone voertuigtechnologieën voor personenauto's kunnen leveren om de externe kosten van uitstoot verminderen. We breiden TREMOVE hiertoe uit met het keuzemodel dat we ontwikkeld hebben in het eerste deel van ons onderzoek.

Aanvullend op deze uitbreiding voorzien we uitstootfactoren voor alternatieve technologieën op basis van MEET (Hickman et al., 1999). Voor elektrische auto's bepalen we de uitstoot die gepaard gaat met de elektriciteitsproductie die nodig is om de batterijen op te laden. Tevens voorzien we in de mogelijkheid om impact op de leefomgeving te vertalen naar een gedifferentieerde heffing evenredig met verschillen in marginale maatschappelijke kosten. Tenslotte vullen we de baseline aan met gegevens over kosten en gebruik van alternatieve technologieën en brandstoffen.

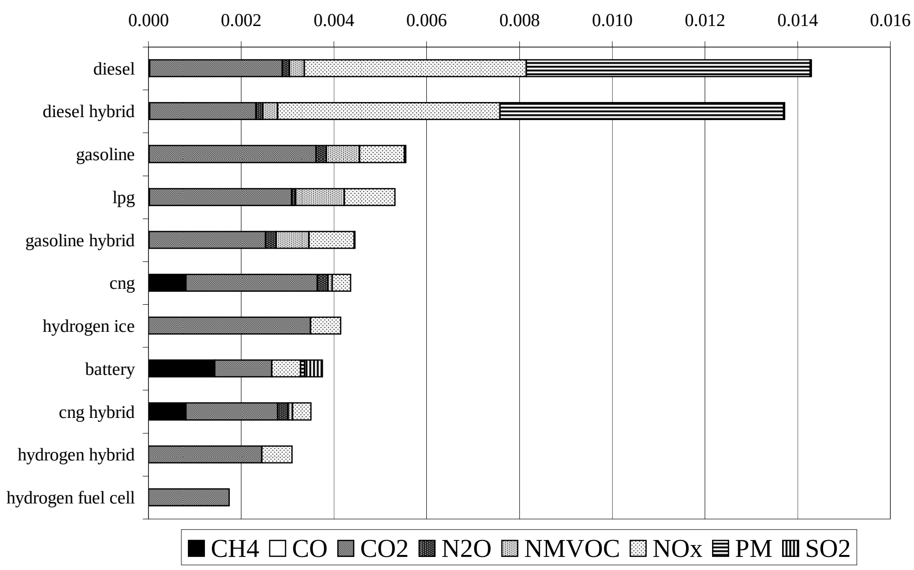
De baseline van het uitgebreide model levert een aantal interessante inzichten. Vooreerst stellen we vast dat alternatieve technologieën zelfstandig een substantieel marktaandeel kunnen verwerven mits voldoende beschikbaarheid. Verder zien we dat de totale uitstoot van vervoersactiviteit afneemt met uitzondering van CO_2 (zie figuur E.2). Alternatieve technologieën hebben zonder uitzondering geringere externe uitstootkosten, maar het verschil met bestaande benzinetechnologie is gering en veel kleiner dan het verschil tussen conventionele benzine- en dieselauto's (zie figuur E.3). Tenslotte kan opgemerkt worden dat het beleid van steeds striktere uitstootnormen tijdens het laatste decennium heeft geresulteerd in een spectaculaire afname van de externe uitstootkosten van diesel- en benzineauto's. Dit beperkt de mogelijkheden tot verdere afname door middel van technologische innovatie.

Omdat we vaststellen dat bestaande heffingen niet overeenstemmen met verschillen in externe uitstootkosten, vervangen we in een eerste simulatie deze bestaande heffingen door een kilometerheffing die voor alle voertuigtechnologieën gelijk is. Dit resulteert in een verschuiving van diesel naar benzineauto's, en in beperktere mate van hybride naar conventionele technologieën. De netto impact op de leefomgeving is positief met een afname van voornamelijk NO_X en PM uitstoot. Dit scenario levert een neutrale basis voor de simulatie van een heffing die een verschuiving naar schone technologieën promoot.

Vervolgens simuleren we de toepassing van een uitstootheffing die gedifferentieerd is naar gebruikte technologie en plaats (binnen of buiten de stedelijke omgeving) en die gelijk is aan de marginale externe uitstootkos-



Figuur E.2. Baseline evolutie van totale vervoersuitstoot (index: 2005 niveau = 100)

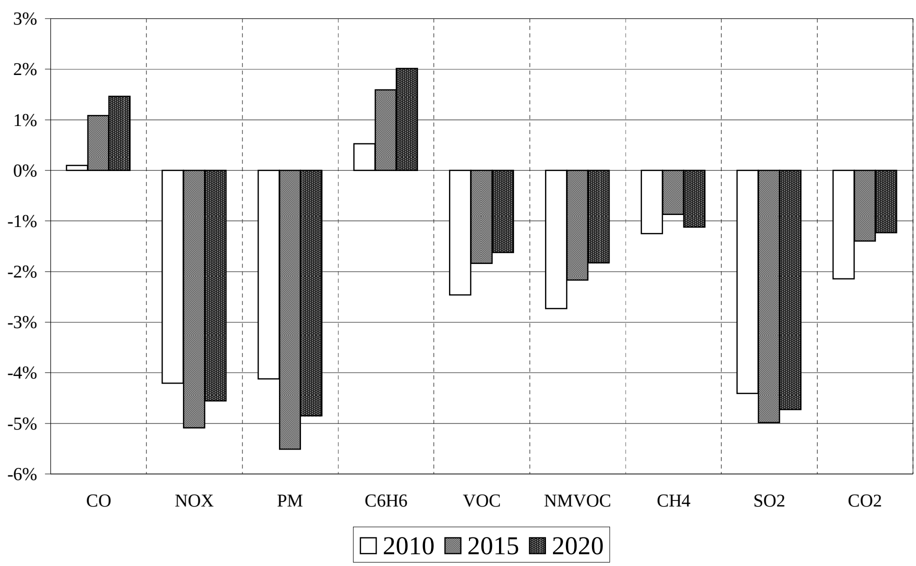


Figuur E.3. Baseline externe kost van uitstoot van nieuwe personenauto's in 2020 (in €/vkm) ten. De heffing komt voor alle technologieën en vervoerswijzen boven op de hierboven beschreven gelijkgestelde kilometerheffing en zorgt ervoor dat voor elke vervoerswijze de verschillen tussen technologieën overeenstemmen met verschillen in externe uitstootkosten. Het beschreven scenario levert een indicatie voor een *first best* evolutie waarvan de welvaartsimpact optimaal is.

Onder de gedifferentieerde heffing zien we dat naast een globale afname van de vervoersactiviteit (van 0,5% voor reizigers tot 3% voor goederen) er ook verschuivingen zijn tussen vervoerswijzen en technologieën. Wanneer op langere termijn het voertuigbestand zich aanpast aan de gewijzigde omstandigheden, gaat een verschuiving tussen vervoerswijzen een beperktere rol spelen.

Binnen het voertuigbestand zien we voornamelijk een verschuiving van diesel- naar benzinetechnologieën, al is de verschuiving eerder gering (grootteorde van een procent punt voor personenauto's). De globale afname van uitstoot bedraagt tot 5% voor PM en NO_X (zie figuur E.4).

Wanneer we de welvaartskost van het scenario becijferen, zien we een netto maatschappelijke winst over de volledige modelleerperiode. De waardering van de impact van de uitstoot toont aan dat op korte termijn de afname voor 65% wordt bereikt door de globale afname van de vervoersvraag, de rest is voornamelijk het gevolg van een verschuiving in technologiegebruik. Slechts 10% van de kostenreductie kan toegeschreven worden aan een verschuiving tussen vervoerswijzen. Op langere termijn stijgt de bijdrage van gewijzigd



Figuur E.4. Impact van uitstootheffing op totale vervoersuitstoot (in % wijziging t.o.v. gelijkgestelde kilometerheffing) technologiegebruik tot ruim 45%, terwijl de bijdrage van verschuiving tussen vervoerswijzen afneemt.

E.3.2. De kostprijs van zuinige auto's

Een tweede reeks simulaties bestudeert de bijdrage die zuinige auto's kunnen leveren tot tegengaan van klimaatverandering en de daaraan verbonden maatschappelijke kost. De bijdrage van het wegvervoer aan klimaatverandering verloopt via de uitstoot van CO_2, wat op zijn beurt nauw verbonden is met het brandstofverbruik. CO_2 is een chemisch erg stabiel gas en bijgevolg niet toxisch. De uitstoot blijft meerdere decennia aanwezig in de atmosfeer. Omdat enkel de globale hoeveelheid CO_2 bepalend is voor klimaatverandering, maakt het niet uit waar en wanneer de uitstoot plaatsvindt, dit in tegenstelling tot andere uitstoot waarvan lokale concentraties bepalend zijn voor de maatschappelijke impact.

Voor de simulaties wordt TREMOVE uitgebreid met een voorstelling van energie-efficiëntie. Enerzijds is er een meerkost verbonden aan de productie van zuinigere wagens, anderzijds is er ook een gedragseffect waar autokopers de zuinigheid van een nieuw voertuig kiezen in functie van de brandstofprijs.

In onze modellering van brandstofefficiëntie kiezen we voor een indirecte benadering op basis van geobserveerd gedrag. De literatuur (zie bijvoorbeeld Brons, 2006; Goodwin, 1992; Johansson and Schipper, 1997; Small and Van Dender, 2006) presenteert waarden voor de elasticiteit die het geobserveerde verband tussen brandstofgebruik en brandstofprijs uitdrukt. Voor ons onderzoek gebruiken we een waarde van $-0{,}2$, wat betekent dat het brandstofverbruik per voertuigkilometer met 2% afneemt wanneer de brandstofprijs met 10% toeneemt.

We nemen aan dat autokopers een voertuig kiezen op basis van totale gebruikskosten, en dat producenten voertuigen bouwen waarvan de gebruikskost geoptimaliseerd is in functie van brandstofefficiëntie. Op basis van deze aannames kunnen we uit de geobserveerde elasticiteit (zie hierboven) de gebruikskosten van voertuigen weergeven als functie van de brandstofefficiëntie.

Om een baseline op te stellen voor brandstofefficiëntie hebben we niet enkel een projectie over de modelleerperiode nodig voor de brandstofprijzen (gebaseerd op PRIMES-transport, zie Knockaert et al., 2002), maar dienen we ook rekening te houden met een zelfstandige verbetering van de brandstofefficiëntie. In dit onderzoek gaan we uit van een jaarlijkse verbetering van 0,6%.

Vervolgens simuleren we een beleid dat uitgaat van efficiëntienormen voor nieuwe voertuigen. We nemen als voorbeeld het EU beleid waarbij rond het jaar 2000 een aantal overeenkomsten werden gesloten met de autoproducenten. Deze akkoorden voorzien dat in minder dan een decennium de gemiddelde CO_2 uitstoot van nieuwe personenauto's gereduceerd wordt tot 140 g/km.

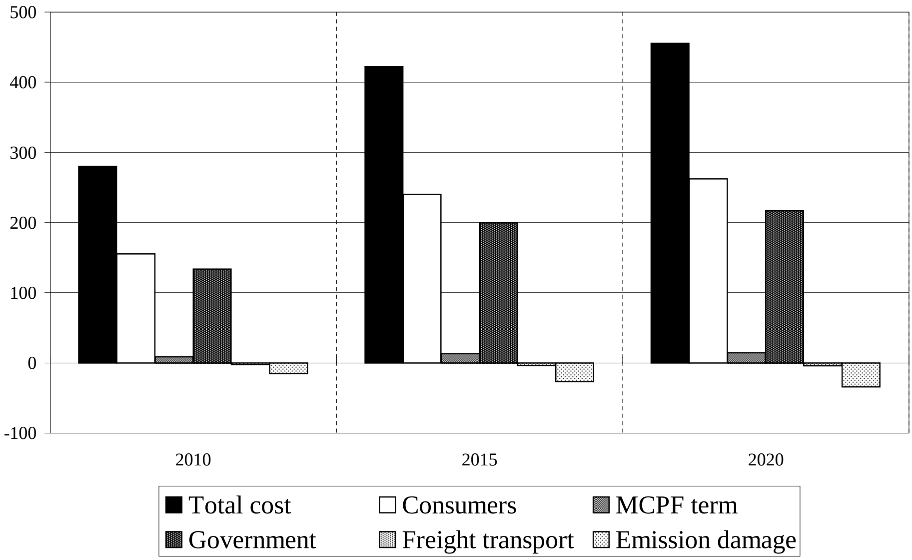
Aansluitend hierop wil de EU het beleid uitbreiden om de uiteindelijke beleidsdoelstelling van 120 g/km te realiseren in 2012.

De beleidssimulatie geeft aan dat een verbetering van de brandstofefficientie van ongeveer 15% nodig is om de beleidsdoelstelling te bereiken. Deze verbetering heeft slechts een beperkte invloed van 1 tot 1,5% op de gebruikskosten (van nieuwe voertuigen), waardoor eerder kleine veranderingen in gebruik van technologieën (van diesel naar benzine) en vervoerswijzen (van auto naar andere) te verwachten zijn. De totale CO_2 uitstoot (alle voertuigen en vervoerswijzen) neemt af met 7%.

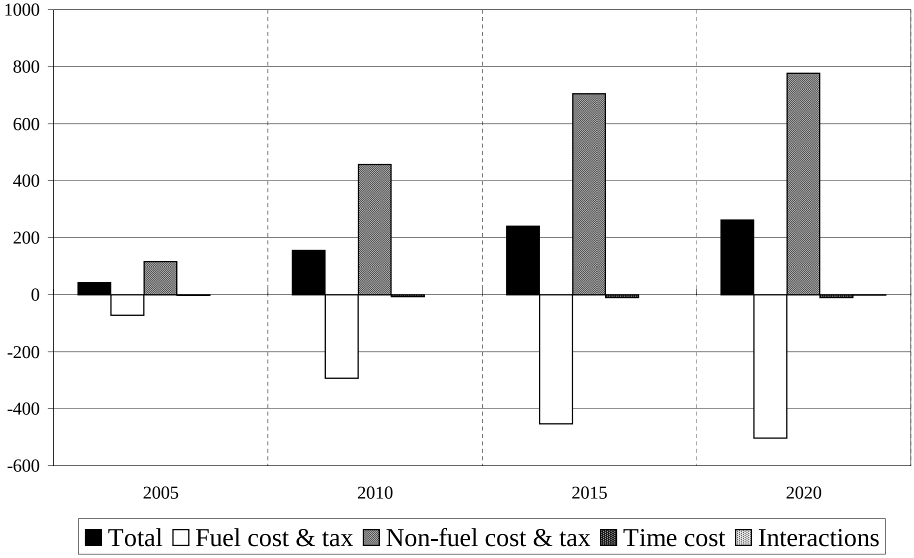
De welvaartskosten van de beleidsmaatregel worden gedragen door de gebruikers én door de overheid (zie figuur E.5). Wanneer autokopers kiezen voor zuinigere voertuigen, betalen ze meer voor het voertuig en minder voor de brandstof (figuur E.6). De heffing op beide componenten is echter niet gelijk, waardoor er een daling is in de overheidsinkomsten.

De totale kost is veel groter dan de winst op het vlak van klimaatverandering: de welvaartskost van de maatregel bedraagt ongeveer 270 €/t in 2010; dit in vergelijking met de externe kost van CO_2-uitstoot die begroot wordt op 5–20 €/t.

In een volgende simulatie bestuderen we het scenario waarin de uitstoot van nieuwe personenauto's verder teruggedrongen wordt tot 120 g/km in 2012. Dit vereist een verbetering van de brandstofefficiëntie van ongeveer 25%. De stijging van de gebruikskosten van nieuwe voertuigen is hier 5%,



Figuur E.5. Jaarlijkse welvaartskost van 140 g/km beleid (in miljoen €2000 t.o.v. baseline)



Figuur E.6. Samenstelling van verandering in consumentensurplus in reizigersvervoer (in miljoen €2000 t.o.v. baseline)

bijgevolg zijn de verschuivingen naar andere vervoerswijzen relatief groter dan in het vorige scenario. Een extra afname van de totale CO_2 uitstoot van 6% is haalbaar in 2020. De maatschappelijke kost van de beleidsmaatregel is 302 €/t, en wordt voornamelijk gedragen door de autokopers.

In een laatste simulatie vergelijken we het EU beleid met een brandstofheffing voor personenauto's. Deze heffing is evenredig met de CO_2 uitstoot en de hoogte ervan is dusdanig gekozen dat de heffing eenzelfde afname in externe kosten van CO_2-uitstoot realiseert tot 2020.

De benodigde heffing zorgt voor een aanzienlijke toename van de brandstofprijzen tot meer dan 2 €/l in 2020. Het is evident dat dergelijke heffing een invloed zal hebben op de vervoersvraag. Ook krijgen we hier reeds een indicatie van het netto welvaartsresultaat als we bedenken dat de heffing overeenkomt met 40 keer de externe uitstootkosten.

De heffing resulteert in een verschuiving van diesel naar benzinevoertuigen, en van autovervoer naar andere vervoerswijzen. De totale vraag naar personenvervoer neemt af met 4% in 2020.

De totale maatschappelijke kosten zijn lager dan bij een uitstootnorm. Alhoewel de autogebruikers aanzienlijk meer gaan betalen, is dit geen welvaartsverlies aangezien de heffingen overeenkomstige inkomsten opleveren voor de overheid. De lagere kosten voor afname van CO_2 uitstoot worden mogelijk gemaakt doordat de heffing toelaat dat de afname wordt gerealiseerd op meerdere manieren en niet enkel via technologische weg. Bij een uitstootnorm blijft de vraag naar vervoer te hoog waardoor grotere technologische inspanningen nodig zijn om het beleidsdoel te realiseren. Bovendien kan de uitstootnorm enkel de uitstoot van nieuwe wagens reduceren, terwijl een heffing ook gebruikers van bestaande voertuigen betrekt.

De netto maatschappelijke kost van de heffing bedraagt 127 €/t. Dit is aanzienlijk lager dan in de EU beleidssimulatie, maar nog steeds boven de externe kosten van CO_2-uitstoot.

E.3.3. Openbaar busvervoer in de stedelijke leefomgeving

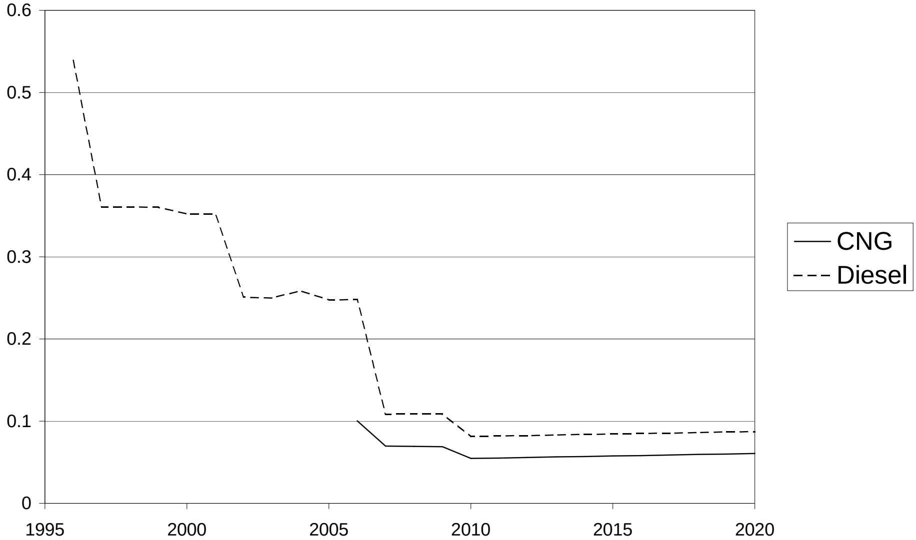
Een laatste reeks simulaties bestudeert mogelijkheden om met voertuigtechnologie de impact van openbaar busvervoer op de stedelijke leefomgeving te verminderen. Hiervoor wordt het TREMOVE model beperkt tot Brussel en worden enkele aanpassingen uitgevoerd in de modellering van het openbaar vervoersaanbod.

Openbaar vervoer verschilt van andere voervoersmarkten in de aanwezigheid van een bijkomende kost in de vorm van wachttijd. Deze wachttijd is functie van het aanbod. Als het aanbod toeneemt, daalt de wachttijd maar stijgen daarentegen de monetaire kosten en uitstoot. De rol van de verschillende aanbodsvariabelen wordt beschreven door Mohring (1972) die het verband aangeeft tussen vervoersvraag, productiekosten en optimaal aanbod en ticketprijs.

In TREMOVE zijn de bezettingsgraden van de verschillende vervoerswijzen extern vastgelegd in de baseline. Het aanbod (in voertuigkilometer) volgt dan steeds de vraag (in reizigerskilometer) in een vaste verhouding. Voor de simulaties waar we specifiek gaan kijken naar openbaar vervoer breiden we TREMOVE uit met de mogelijkheid om voor bus- en spoorvervoer bezettingsgraad (en aanbodvolume) en ticketprijs te optimaliseren in functie van vraag- en aanbodsvariabelen. Daarbij voorzien we tevens in de mogelijkheid om de uitstoot externaliteit te internaliseren. De baseline voor Brussel wordt overeenkomstig bijgewerkt voor het openbaar vervoersaanbod (bus en spoor).

Net als bij personenwagens stellen we vast dat het beleid van steeds striktere uitstootnormen voor busvoertuigen over de afgelopen decennia reeds heeft gezorgd voor een spectaculaire afname van de impact op de stedelijke leefomgeving (zie figuur E.7). Niettemin blijft busvervoer per reizigerskilometer een grotere impact hebben op de leefomgeving in vergelijking met benzineauto's. Op korte termijn zijn zelfs dieselauto's schoner, voornamelijk omdat bussen een langere levensduur hebben en daardoor oudere en minder schone voertuigen langer in het bestand blijven.

In een eerste simulatie optimaliseren we ticketprijzen en aanbodsvolume zonder rekening te houden met de uitstootexternaliteit. Het geoptimaliseerde aanbod leidt tot aanzienlijk lagere ticketprijzen bij een hoger aanbod. De frequentie stijgt voornamelijk in de daluren: door het toewijzen van capaciteitskosten (inclusief voertuigen) aan de piekperiode zijn de productiekosten



Figuur E.7. Baseline evolutie van impact op stedelijke leefomgeving van nieuwe busvoertuigen (in €/vkm)

tijdens de daluren veel lager. Dergelijke resultaten komen overeen met eerdere bevindingen (De Borger and Wouters, 1998). Naast een belangrijke stijging in het OV gebruik, leidt dit tevens tot een daling van 12% in het autogebruik. Netto is er een welvaartswinst, en ook de impact op de leefomgeving neemt af doordat autovervoer gedeeltelijk wordt vervangen door elektrisch spoorvervoer.

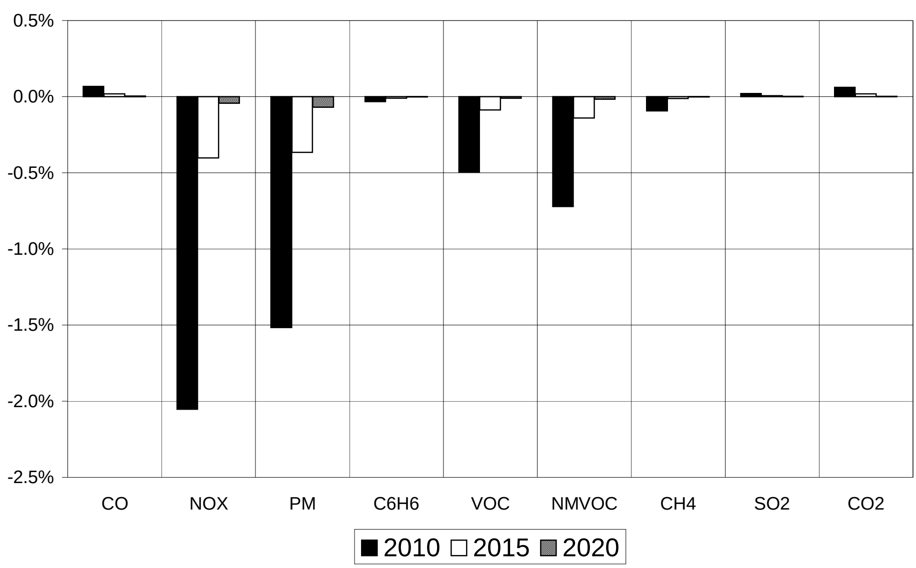
In een tweede simulatie optimaliseren we opnieuw de openbaar vervoer aanbodsvariabelen, maar deze keer verrekenen we in de optimale ticketprijzen en het aanbodsvolume de externe kosten van uitstoot. We vergelijken de resultaten met de eerste simulatie. Hierbij valt meteen op dat de impact op de leefomgeving slechts beperkt wordt verrekend in de ticketprijs. Een groter deel van de externaliteit wordt voor de reiziger in rekening gebracht via de wachttijd. Op die manier wordt het aanbod in 2010 met 12% verminderd terwijl de vraag slechts met 2% afneemt. De totale uitstoot neem af met ongeveer een procent. Opvallend is hier dat het scenario een maatschappelijke winst oplevert voornamelijk door verstoringen op andere markten (inkomsten uit heffingen personenwagens en MCPF term). In de volgende simulaties gebruiken we dit scenario als referentie om de bijdrage van voertuigtechnologieën te bestuderen.

In een derde simulatie bestuderen we het scenario waarbij oudere voertuigen worden aangepast zodat ze voldoen aan de uitstootnormen van nieuwe voertuigen. Doordat bussen een relatief lange levensduur hebben in vergelijking met andere wegvoertuigen, en door de sterke vooruitgang die geboekt is op het vlak van uitstootnormen, is dit een waardevolle toepassing. Voor de simulatie nemen we aan dat Euro 2 voertuigen worden bijgewerkt naar Euro 5. We zien dat deze aanpassing een vermindering oplevert van de totale vervoersuitstoot van 1,5 (PM) tot 2% (NO_X) in 2010 (zie figuur E.8). Na 2010 neemt de impact snel af wanneer de oude voertuigen alsnog uit het bestand verdwijnen. Het scenario levert een netto maatschappelijke winst op wanneer de impact op de leefomgeving wordt meegerekend.

In een laatste simulatie bestuderen we de vervanging van dieselbussen door voertuigen aangedreven met aardgas (CNG). Dit scenario levert een reële afname op van de vervoersuitstoot. Echter zijn de technologiekosten relatief hoog waardoor het scenario resulteert in een netto kost.

E.4. Besluit en beleidsaanbevelingen

De *analyse* van het aankoopgedrag van auto's op basis van een keuze-experiment levert inzicht in de voorkeuren die autokopers hebben voor nieuwe technologieën. De invloed van verschillende technologie-eigenschappen werd geanalyseerd. Daarbij werd voor de meeste onderzochte variabelen een significante invloed vastgesteld. Echter voor de hybride eigenschap van technologieën werden geen voorkeuren vastgesteld. Op basis van de geschatte gedragsmodellen kon worden afgeleid dat autokopers bereid zijn om meer te betalen voor schonere technologieën, alhoewel uit de focusgroep bleek dat autokopers geen correcte inschatting maken van de relatieve impact op de



Figuur E.8. Impact van aanpassing oude busvoertuigen op totale vervoersuitstoot leefomgeving van verschillende voertuigtechnologieën.

De analyse met behulp van gemengde logit modelspecificaties liet toe om rekening te houden met het specifieke karakter van het keuze-experiment waarin deelnemers herhaalde keuzes maken. Daarbij werden correlatiepatronen in voorkeuren voor technologieën onderzocht, zowel voor nieuwe als conventionele.

Het gebruik van gemengde geneste logit specificaties laat toe om correlatiepatronen te identificeren op basis van het keuze-experiment en die vervolgens (benaderend) te reproduceren met een eenvoudig geneste logit simulatiemodel voor enkelvoudige keuze. De methodologie om dit simulatiemodel te ontwikkelen werd gepresenteerd en toegepast voor een simulatiemodel dat kan gebruikt worden in het TREMOVE vervoersmodel.

De *simulatie* van technologische en andere maatregelen om uitstoot van wegvervoer te verminderen werd uitgevoerd met behulp van een aangepaste versie van het vervoersmodel TREMOVE waarvoor een baseline voor België ontwikkeld werd.

De baseline geeft aan dat zonder nieuwe maatregelen reeds een afname van uitstoot te verwachten is, voornamelijk door reeds geïntroduceerde en steeds striktere uitstootnormen voor nieuwe voertuigen. De maatschappelijk waardering van de resterende externe kosten van uitstoot is eerder klein op voertuigniveau. De enige uitzondering is de totale uitstoot van CO_2 die in de baseline stijgt.

Alternatieve voertuigtechnologieën voor personenauto's hebben een significant lagere impact op de leefomgeving. De verschillen met bestaande technologieën zijn echter niet groot, bijgevolg heeft een (efficiënte) gedifferentieerde uitstootheffing eerder beperkte mogelijkheden. Wel stellen we vast dat de bestaande differentiëring tussen diesel en benzine niet overeenstemt met verschillen in impact op leefomgeving, het gelijkstellen van de heffing voor beide technologieën kan zowel voor de leefomgeving als voor de maatschappij een netto winst opleveren.

De afname in externe kosten van uitstoot resulteert op korte termijn voornamelijk van een afname van de vervoersvraag. Op langere termijn gaat ook de verschuiving tussen technologieën een rol spelen. Een verschuiving tussen vervoerswijzen levert slechts een beperkte bijdrage in het scenario van een uitstootheffing.

De CO_2 uitstoot van personenauto's is nauw verbonden met het vraagstuk van energie-efficiëntie. De beleidsaanpak waarbij (gemiddelde) uitstootnormen worden opgelegd aan nieuwe auto's blijkt wel effectief maar niet efficiënt. De kosten per eenheid CO_2 afname zijn een veelvoud van de overeenkomstige externe maatschappelijke kost. Zelfs wanneer gekozen zou worden voor een beleid van uitstootheffingen, blijven de kosten te hoog. De belangrijkste reden is dat de traditionele brandstofkosten reeds veel hoger zijn dan de maatschappelijke kosten van CO_2 uitstoot.

Ook voor stedelijk busvervoer kunnen technische maatregelen bijdragen aan een uitstootreductie. De relatief lange levensduur van de voertuigen maakt het zinvol om oudere bussen te reviseren zodat ze aan striktere uitstootnormen voldoen. Deze maatregel blijkt effectief en efficiënt. Voor aardgasbussen daarentegen blijken de kosten groter dan de voordelen van de lagere uitstoot.

Een *beleid* gebaseerd op technologische maatregelen blijkt in alle gevallen effectief. In het verleden is op deze manier een aanzienlijke afname van de uitstoot van wegvervoer gerealiseerd. Men kan verwachten dat eenzelfde beleid succesvol gevoerd kan worden rond vervoerswijzen die tot nog toe buiten beeld bleven.

De simulaties waarin de uitstootexternaliteit met een heffing wordt geïnternaliseerd geven aan dat technologieën een belangrijke rol spelen in een efficiënt beleid waarin rekening gehouden wordt met de volledige maatschappelijke kosten en baten van het gevoerde beleid. Wanneer technologiekosten te hoog worden is het echter niet mogelijk om een netto maatschappelijke winst te realiseren.

De maatschappelijke kost van een afname van CO_2 uitstoot in autoverkeer blijkt erg hoog te liggen. Wellicht is het aan te bevelen om eerst in andere sectoren te komen tot een afname van de uitstoot.

In verschillende scenario's blijkt een verschuiving van diesel- naar benzineauto's wenselijk. Een eenvoudige maatregel om dit te realiseren is het wegwerken van verschillen in bestaande heffingen.

Tenslotte merken we op dat een verschuiving tussen vervoerswijzen in de meeste scenario's slechts een beperkte bijdrage levert tot afname van uitstoot.

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- Knockaert, J., Meire, E. & Proost, S. (2004) Environmental and economic evaluation of fiscal transport policy measures, Presented at the 13th Annual Conference of the European Association of Environmental and Resource Economics (EAERE), Budapest, Hungary, 25–28 June.

- Knockaert, J., Van Regemorter, D. & Proost, S. (2004) Analysis of transport policy scenarios for EU-countries with PRIMES-transport, Presented at the 10th World Conference on Transport Research, Istanbul, Turkey, 4–8 July.

- Knockaert, J. (2005) The Choice for Alternative Cars, Presented at the 14th Annual Conference of the European Association of Environmental and Resource Economics (EAERE), Bremen, Germany, 23–26 June.

- Knockaert, J. (2005) Do we want cleaner cars? Presented at the BIVEC-GIBET Transport Research Day 2005, Diepenbeek, Belgium, 30 November.

- Knockaert, J. (2007) The welfare cost of more fuel efficient cars. Presented at the 11th World Conference on Transport Research, Berkeley, CA, 24–28 June

- Knockaert, J., Rouwendal, J. & Verhoef, E. (2008) The Spitsmijden experiment: a reward to battle congestion. Presented at the 88th Annual Meeting of the Transportation Research Board (TRB), Washington, DC, 11–15 January

Chapters in Books

- Knockaert, J. & Proost, S. (2005) Transport Sector, in Willems, B., Eyckmans, J. & Proost, S., eds. 'Economic Aspects of Climate Change Policy, A European and Belgian Perspective', ACCO, Leuven, pp. 99-110

Research reports (selection)

- Knockaert, J., Van Regemorter, D. & Proost, S. (2002) Transport and energy scenarios for EU15 countries + Switzerland and Norway - an analysis with the PRIMES-transport model, Final report

- Design & production of CONPASS toolbox (CD & website) with Ben Immers (2002)

- Proost, S., Meire, E. & Knockaert, J. (2004) Hervorming transportfiscaliteit in Vlaanderen, Steunpunt Bestuurlijke Organisatie Vlaanderen (SBOV)

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- De Ceuster, G., Franckx, L., Van Herbruggen, B., Logghe, S., Van Zeebroeck, B., Tastenhoye, S., Proost, S., Knockaert, J., Williams, I., Deane, G., Martino, A. & Fiorello, D. (2005) Tremove - tremove 2.30 model and baseline description, Final Report Service Contract B4-3040/2003/366851/MAR/C.1, European Commission - DG ENV - Directoracte C - Air and Chemicals.

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- Knockaert, J., Bliemer, M., Ettema, D., Joksimovic, D., Mulder, A., Rouwendal, J. & van Amelsfort, D. (2007) Experimental design and modelling: Spitsmijden

- Knockaert, J., Wieland, B., Evangelinos, C. & Rietveld, P. (2008) Economic theory and methodology on differentiated infrastructure charging, Deliverable 3.3 of DIFFERENT project, EU Commission

Master Thesis

- Knockaert, J. (1999) Ontwerp van een openbaar vervoernet voor het stadsgewest Antwerpen, K.U.Leuven, Leuven

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Jasper Knockaert was born on 25 November, 1975, in Antwerp (Belgium). After finishing secondary school at the Sint-Lambertuscollege in Westerlo (Belgium) he started engineering studies at the K.U.Leuven in 1994. He graduated as a civil engineer in 1999. His master thesis "Ontwerp van een openbaar vervoernet voor het stadsgewest Antwerpen" was supervised by prof. Ben Immers. The same year he started a post-graduate in business economics at the K.U.Leuven which he finished in 2000.

In February 2000, he joined the Traffic research group at the Department of Civil Engineering of the K.U.Leuven to work on the CONPASS EU research project till mid-2002. The focus of the project is on regional cross-border public transport.

From January 2001 till April 2006, he was affiliated with the ETE research group (Energy, Transport and Environment) at the Department of Economics of the K.U.Leuven to work on several Belgian and EU research projects with a focus on economic and technical analysis of emission technologies in road transport.

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