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**Development of a stochastic
optimization approach to determine
cost-efficient environmental
protection strategies**

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Schieberle**

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Development of a stochastic optimization approach to determine cost-efficient environmental protection strategies

Case study of policies for the future European passenger
transport sector with a focus on rail-bound and on-road
activities

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Contents

Abstract	v
Kurzfassung	vii
List of Figures	ix
List of Tables	xv
List of Acronyms	xxiv
List of Symbols	xxix
I Background and methodology	1
1 Introduction and contributions	3
1.1 Motivation	3
1.2 Objectives	5
1.3 Background on assessment methodologies	6
1.4 Related work	9
1.4.1 GAINS	9
1.4.2 OMEGA-2 and OMEGA-O ₃	12
1.4.3 RIAT	18
1.4.4 ExternE and UWM	21
1.5 Contributions of this thesis	22
2 Methodology	27
2.1 System boundaries	27
2.2 Deterministic model formulation	28
2.2.1 Objective function	29
2.2.2 Identity equations	33
2.2.3 Externalities	41
2.3 Stochastic model formulation	48

2.4	Piecewise-linear approximation of non-linear terms	50
2.5	Representing risk attitudes in the objective function	53
2.5.1	Existing approaches to measure risk of decisions	54
2.5.2	Objective function under specific risk attitude	57
II	Case study	61
3	Environmental data and their uncertainty	63
3.1	Reference demand and activity levels	63
3.1.1	Basic reference activity	63
3.1.2	Development of mode-specific Lorenz curves	67
3.1.3	Distribution of vehicle stock and mileage over socio-economic groups	76
3.2	Data and uncertainty of emission factors	81
3.2.1	On-road transport	81
3.2.2	Rail-bound transport	88
3.3	Uncertainty of air quality modelling	90
3.3.1	Baseline and projected air quality levels	91
3.3.2	Intra-model uncertainty of atmospheric models	92
3.3.3	Parametrized modelling of air quality gradients	99
3.4	Data and uncertainty of exposure-response modelling	102
3.4.1	Exposure-response relationships	102
3.4.2	Monetization of impacts	108
3.5	Uncertainty of the impact and monetization of climate forcing gases . . .	111
3.5.1	Uncertainty of the global warming potential	111
3.5.2	Issues in valuing the impacts of climate change	112
3.5.3	Uncertainty of monetization	113
4	Policies eliciting behavioural change	115
4.1	Overview of past reviews on transport elasticities	116
4.2	Data collection of transport demand elasticities	119
4.3	Meta-regression models of transport policies	123
4.3.1	Fuel price: Effects on public transport demand	125

4.3.2	Urban bus fares: Effects on car travel and rail-bound public transport demand	128
4.3.3	Urban rail-bound transit fares: Effects on car travel and bus demand	132
4.3.4	Road pricing: Effects of city tolls on car travel demand and public transport	136
4.3.5	Non-urban train fares: Effects on non-urban car travel demand and coach demand	137
4.3.6	Non-urban coach fares: Effects on non-urban individual motorized and rail-bound transit demand	139
4.4	Income-dependent elasticity estimates	141
5	Technical options and command-and-control regulations	145
5.1	Reduction of NOx exhaust emissions	145
5.1.1	Software patches for passenger cars and vans	147
5.1.2	BNOx-SCR for passenger cars and vans	149
5.1.3	BNOx-SCR for buses	152
5.2	Ultra low-emission zones in cities along with a scrapping bonus	153
5.3	Retrofitting particulate filters	156
	III Results	159
6	Results and discussion	161
6.1	General remarks	161
6.2	Scenario set-up	163
6.3	NOx reduction goals	167
6.4	Impact of risk aversion vs. risk neutrality	173
7	Conclusions and outlook	181
7.1	Revisiting the objectives	181
7.2	Limitations of the approach with respect to treatment of uncertainty	182
7.3	Future research directions	185

A Appendix	189
A.1 Model input disaggregation	189
Bibliography	193

Abstract

Recurrent violation of air quality standards detected at measuring stations worries city authorities across Europe. Accompanied by the recent disclosure of large-scale irregularities in real driving vehicle emissions air pollution control has nowadays taken on greater significance than ever before. Decision-makers aim to reduce the amount adverse effects of polluted air and climate change simultaneously by implementing proper legislation. However, they face severe uncertainties when estimating both people's response to policies and the resulting environmental impact. Obviously, this imposes risk on achieving the desired effect. Furthermore, failure to succeed in reducing the adverse impacts lowers acceptance of policies among the general public.

Recent studies in this field do not sufficiently account for this risk and ignore a decision-maker's level of risk-aversion when recommending policies: While some of the studies acknowledge the existence of large uncertainties in impact estimation, they do not adequately incorporate current knowledge in the analysis. Some studies use expected values only during the optimization approach which leads to results that cannot be considered recommendations for risk-averse decision-makers. Other approaches deliberately overestimate costs in the presence of uncertainty and even exclude uncertain aspects of the assessment entirely from the analysis (cf. [Amann et al. \(2011\)](#)).

This work, by contrast, aims at contributing to overcome these limitations. This is achieved by incorporating risk attitudes in the objective function of a newly developed stochastic optimization approach which properly accounts for different levels of risk-aversion. Furthermore, the approach is able to handle the optimal selection and parametrization of both technical options and non-technical measures. Thereby, it determines cost-efficient environmental protection strategies by trading off avoided adverse health effects and climate impacts against induced cost and utility losses.

Passenger transport is traditionally considered a representative example for sectors in which considerable technical progress has already been achieved. Therefore, non-technical measures are recognized as important means for decision-makers to induce behavioural change to achieve further improvement. However, current studies in the context of integrated assessment modelling (IAM) focus solely on technical options due to their comparably simple assessment in terms of cost-effectiveness or cost-efficiency. To be able to

properly model uncertain behavioural response to policies an extensive meta-regression analysis (MRA) was conducted in the scope of this thesis. Additionally, several promising technical options are addressed which specifically target reduction of NO_x emissions. These gain in importance in light of the recent emission scandal involving the disclosure of some diesel engines being presumably programmed to activate specific emission controls only when under laboratory testing.

A stochastic optimization approach to determine cost-efficient environmental protection strategies via cost-benefit analysis (CBA) is developed in this thesis. Furthermore, it is integrated into a novel modelling framework that incorporates uncertainty of environmental impacts as well as uncertainty of people's response to policy in a consistent manner. Policy intervention is modelled via implementation of both technical and non-technical measures. A case study is conducted and its results are presented and discussed. It investigates how further improvements can be achieved in the passenger transport sector of the 28 EU member states plus Norway and Switzerland.

All scenarios addressed in this thesis show positive expected net benefit. Risk aversion results in 57.7 (44.6; 86.4) billion € net benefit whereas a higher value of 84.3 (43.5; 149.2) billion € can be reached under risk-neutral stance. It becomes evident that NO_x reduction goals (minus 25% and minus 75%) will not achieve higher net benefit when compared to social welfare maximization without constraints. One may conclude that the implementation of technical measures is key under risk-averse stance. This is mainly due to the comparably lower overall uncertainty with respect to the impact of non-technical measures.

Kurzfassung

Wiederholte Verstöße gegen Luftqualitätsnormen an Messstationen beunruhigen die zuständigen städtischen Behörden in ganz Europa. Durch die jüngste Enthüllung von Unstimmigkeiten bei Emissionen im praktischen Fahrbetrieb hat die Reinhaltung der Luft heute größere Bedeutung als je zuvor. Entscheidungsträger versuchen daher, die Schäden durch Luftverschmutzung sowie durch den Klimawandel mittels geeigneter Rechtsvorschriften zu verringern. Hierbei gibt es jedoch große Unsicherheiten sowohl bezüglich der Abschätzung der Reaktion auf politische Maßnahmen als auch bezüglich der resultierenden tatsächlichen Umweltbeeinflussung. Dies birgt Risiken hinsichtlich des Erreichens der gewünschten Wirkung. Vermag eine Maßnahme nicht, negative Auswirkungen zu verringern, sinkt zudem die Akzeptanz in der breiten Öffentlichkeit.

Bestehende Arbeiten in diesem Bereich tragen diesem Risiko nicht ausreichend Rechnung und beziehen dadurch die Risikoaversion eines Entscheidungsträgers nicht genügend in Empfehlungen mit ein. Manche Studien würdigen zwar die Existenz großer Unsicherheiten bei der Abschätzung von Umweltauswirkungen, berücksichtigen diese aber nicht hinreichend in der Analyse: Einige Arbeiten verwenden nur Erwartungswerte während des Optimierungsprozesses, was zu Empfehlungen führt, die für risiko-averse Entscheidungsträger nicht geeignet sind. Andere Verfahren setzen in der Gegenwart von Unsicherheiten absichtlich Kosten zu hoch an und schließen sogar teilweise unsichere Aspekte der Bewertung komplett von der Analyse aus (vgl. [Amann et al. \(2011\)](#)). Diese Arbeit hingegen macht sich zum Ziel, dazu beizutragen, diese Grenzen bestehender Arbeiten zu überwinden. Dies gelingt durch die Einbeziehung der Risikobereitschaft in die Zielfunktion eines neuentwickelten stochastischen Optimierungsverfahrens. Darüber hinaus ist der Ansatz in der Lage, die optimale Auswahl und Parametrisierung von sowohl technischen als auch nicht-technischen Maßnahmen vorzunehmen. Durch das Abwägen von Gesundheits- und Klimaschäden mit Kosten und Nutzenverlusten ermittelt das Verfahren effiziente Umweltschutzstrategien.

Der Personenverkehr wird klassischerweise als Beispiel für Sektoren genannt, in welchen bereits beträchtlicher technischer Fortschritt erzielt wurde. Um mittels Verhaltensänderung der Bevölkerung weitere Verbesserungen zu erreichen, werden nicht-technische Maßnahmen als wichtiges Hilfsmittel für Entscheidungsträger angesehen. Dennoch kon-

zentrieren sich bestehende Arbeiten im Bereich integrierter Bewertungsmodelle lediglich auf technische Möglichkeiten, da sich diese vergleichsweise einfach hinsichtlich ihrer Kosteneffektivität und -effizienz beurteilen lassen. Um in der Lage zu sein, unsichere Verhaltensreaktion auf Politiken angemessen zu modellieren, wurde im Rahmen dieser Arbeit eine umfangreiche Meta-Regressionsanalyse durchgeführt. Zusätzlich werden einige vielversprechende technische Möglichkeiten betrachtet, die explizit auf die Minimierung von NO_x -Emissionen abzielen. Diese Maßnahmen werden insbesondere im Hinblick auf den jüngsten Emissionsskandal immer bedeutender: Es wird vermutet, dass einige Dieselmotoren darauf programmiert sind, bestimmte Abgasreinigungsanlagen nur unter Testbedingungen zu verwenden. Als Folge dieser Enthüllung wurden zahlreiche Hersteller beschuldigt, bei ihren Motoren ähnlich zu verfahren.

In dieser Arbeit wird ein stochastisches Optimierungsverfahren zur Ermittlung effizienter Umweltschutzstrategien mittels Kosten-Nutzen-Analyse entwickelt. Des Weiteren wird dieses in einen Modellierungsrahmen integriert, welcher in konsistenter Weise die Unsicherheiten von Umweltwirkungen und die Unsicherheiten von Verhaltensreaktion auf Rechtsvorschriften berücksichtigt. Politische Eingriffe werden mittels Implementierung von sowohl technischen als auch nicht-technischen Maßnahmen modelliert. Zudem wird eine Fallstudie durchgeführt und die Ergebnisse dargestellt. In dieser wird untersucht, wie weitere Verbesserungen im Personenverkehrssektor der 28 Mitgliedsstaaten der Europäischen Union, Norwegen und der Schweiz erreicht werden können.

Alle betrachteten Szenarien zeigen einen positiven erwarteten Nettonutzen. Unter Risikoaversion ergeben sich 57,7 (44,6; 86,4) Mrd. €, wobei ein höherer Wert von 84,3 (43,5; 149,2) Mrd. € unter Risiko-Neutralität erreicht werden kann. Zudem zeigt sich, dass NO_x -Reduktionsziele (minus 25% und minus 75%) zu keinem positiven Nutzen gegenüber dem Ziel der Wohlfahrtsoptimierung ohne Nebenbedingung führen. Generell lässt sich zudem beobachten, dass technische Maßnahmen in risiko-aversen Szenarien einen höheren Stellenwert im Vergleich zu nicht-technischen Maßnahmen haben. Dies lässt sich auch auf die geringere Unsicherheit in Bezug auf ihre Auswirkung zurückführen.

List of Figures

Figure 2-1	A stylised distribution of net benefit. For the specific distribution the expected value, value-at risk, and conditional value-at risk are indicated. It is important to recognize that the distribution of net benefit itself depends on the policy selection and, hence, on the objective function.	58
Figure 3-1	Projected reference demand [million person-kilometres (PKMs)] of different vehicle categories in 2030. Figure shows peak vs. off-peak and central activity district vs. general urban area.	65
Figure 3-2	Occupancy rates (OR) of cars, trains/metro/tram and buses/coaches for European Union, Norway and Switzerland (EU28+2) as derived from the TREMOVE model. The data are distinguished by region and time of the day.	66
Figure 3-3	Lamé curves with $a = b = 1$ for various values of k (on the left) and function $L(r)$ after setting $L = y$ and $x = 1 - r$ (Source: Henle et al. (2008)).	69
Figure 3-4	Lorenz curves derived via Bayesian model averaging (BMA) for three common modes of transport, namely cars, passenger trains and buses. The figures in the upper row show models for Germany (DE) and the figures in the lower row show models for Norway (NO). The dark-coloured line shows the expected curve derived via BMA and the light-coloured lines show the individual models whereas the alpha value indicates the probability of the individual model.	71
Figure 3-5	Share of PKM per income quintile (Q1 to Q5) per mode of transport and per country. The values were derived by the country- and mode-specific Lorenz curves described in the text. Note that there is no rail-bound traffic in Cyprus (CYP) and Malta (MLT).	74
Figure 3-6	Share of person-kilometres driven in a certain vehicle category per income quintile (Q1 to Q5) per country. Note that there is no rail-bound traffic in Cyprus (CYP) and Malta (MLT).	75

Figure 3-7	Share of fuel type and emission standard on the total person-kilometres driven by individual traffic (cars, vans and motorcycles) per income quintile (Q1 to Q5) and per country. There is a tendency of vehicle complying with 'older' emission standards (i.e. pre-Euro 4 and Euro 4) to be operated by lower income groups, and a tendency of 'newer' emission standards (i.e. Euro 5 and Euro 6) being present in mid-income and higher income groups.	79
Figure 3-8	Average vehicle age (cars only) for income quintiles per country. A common pattern across countries is decreasing age with increasing income.	80
Figure 3-9	Mean reference emission factors [g/PKM] of diesel-fuelled passenger cars stratified by fuel, emission standard and pollutant (uncertainties not shown).	83
Figure 3-10	Mean reference emission factors [g/PKM] of gasoline-fuelled passenger cars stratified by fuel, emission standard and pollutant (uncertainties not shown).	84
Figure 3-11	Scatter-plot of observed and predicted $PM_{2.5}$ annual average in 2005 ($R^2 = 0.87$, $N = 98$). Observations were made at ground-based stations. Predictions were made by a random-forest model. Input variables are ranked by importance given as the increase of mean-square error (MSE) occurring when removing one of the variables individually (PM_{10} = Observed PM_{10} level; POPD = Population density; LON = Longitude; LAT = Latitude; WIND = Wind speed at 10m; RELH = Relative humidity; SFCR = Surface roughness; TEMP = Temperature at 2m).	94
Figure 3-12	Estimated projected reduction of baseline $PM_{2.5}$ levels until 2030. The reduction was estimated using results of a model ensemble as described in this document. Mean (left) and standard deviation (right) are given whereas the deviation stems is due to different model formulations only (driven by same data).	95
Figure 3-13	μ_g (geometric mean) and σ_g (GSD) of four modelled urban $PM_{2.5}$ levels compared to AirBase measurements in 2005.	97

Figure 3-14 μ_g (geometric mean) and σ_g (GSD) of four modelled rural PM _{2.5} levels compared to AirBase measurements in 2005.	97
Figure 3-15 μ_g (geometric mean) and σ_g (GSD) of four modelled urban NO ₂ levels compared to AirBase measurements in 2005.	98
Figure 3-16 μ_g (geometric mean) and σ_g (GSD) of four modelled rural NO ₂ levels compared to AirBase measurements in 2005.	98
Figure 3-17 Source-receptor matrices for Germany based due to one ton reduction of volatile organic compound (VOC) (V) and changes at surface level (<2m). The figures show change of PM2.5 [$\mu\text{g}/\text{m}^3$] on the left and change of NO ₂ [ppb/ m^3] on the right. The difference is shown relative to a base year but with varying meteorological conditions of five years from 2006 to 2010.	100
Figure 3-18 Source-receptor matrices for Germany based on 2006 meteorology and changes at surface level (<2m). The figures show change of PM2.5 [$\mu\text{g}/\text{m}^3$] on the left and change of NO ₂ [ppb/ m^3] on the right. The changes are due to one ton emissions change of one of the following five precursors respectively: Ammonia (A), nitrogen oxides as NO ₂ (N), primary fine particles <2.5 μm aerodynamic diameter (P), sulphur oxides as SO ₂ (S) and VOC (V).	101
Figure 3-19 European population aged 25 to 69. Projection from 2015 onwards. Uncertainty remains very low until about 2040. The 95% confidence intervals (CIs) of the probabilistic projection are indicated by the red dotted lines.	107
Figure 3-20 Marginal abatement costs as a convex function of implied stabilisation target (Source: Kuik et al. (2009)).	114
Figure 4-1 Historical data availability of transport elasticities estimates per major world region based on the collection period mentioned in the individual study. If the study spans a longer period, the median year was used. If no period was mentioned, the publication date was used instead.	121

Figure 4-2	Overview of four important characteristics of the elasticity estimates derived from the studies investigated. The lack of complete information for each estimate calls for a method of imputing these data. . . .	121
Figure 4-3	Country-specific short-term public transport demand cross-elasticity of fuel price as derived from the regression model as a function of wealth (gross domestic product (GDP) at purchasing power parity (PPP) per capita), urbanization (population density) and attractiveness of public transport (rail kilometres per country area).	127
Figure 4-4	Country-specific car travel demand cross-elasticity of bus fares as derived from the regression model for urban areas.	131
Figure 4-5	Country-specific rail-bound travel demand cross-elasticity of bus fares as derived from the regression model for urban areas.	131
Figure 4-6	Country-specific urban car travel demand cross-elasticity of train fares as derived from the regression model.	135
Figure 4-7	Country-specific urban bus travel demand cross-elasticity of train fares as derived from the regression model.	135
Figure 4-8	Non-urban individual travel cross-elasticity demand with respect to train fare.	139
Figure 6-1	Technology distribution within fleet of diesel-fuelled cars and vans in urban areas across Europe. The lower two scenarios have low-emission zones (LEZs) in place. The figure shows technology distribution in the reference case (top), social-welfare optimum (2nd from top), and with NOx reduction goals of 25% (3rd from top) and 75% (bottom) as a result of taking different measures.	169
Figure 6-2	Technology distribution within city bus fleet across Europe. Note that public buses are exempt from LEZ regulation and NOx reduction goals. The figure shows technology distribution in the reference case (top) and with NOx reduction goals of 75% (bottom) as a result of taking cost-efficient measures. Others are mostly compressed natural gas (CNG) or hybrids.	170

Figure 6-3	Modelled net benefit, avoided damages, utility loss, subsidies and technology cost given for six different NO _x reduction scenarios (x-axis). Values are given in billion €. Box-Whisker plots of show median (bold horizontal line), mean (red dot), middle 50% of the results (box), data points without outliers (vertical lines), and outliers (black dots).	172
Figure 6-4	Modelled net benefit, avoided damages, utility loss, subsidies and technology cost given for for different values of ϕ (x-axis). Values are given in billion €. Box-Whisker plots of show median (bold horizontal line), mean (red dot), middle 50% of the results (box), data points without outliers (vertical lines), and outliers (black dots).	174
Figure 6-5	Recommended distance-based city toll from 0 to 0.40 Euro/PKM (additional cost) within central activity districts (CADs) under NR75. The figure shows respective toll for passenger cars (PCs) (left) and vans (right) in the risk-neutral case (NEUT, blue) and the risk-averse case (AVRS, red). Overlap is shown in purple.	176
Figure 6-6	Recommended fuel cost adjustment under NR75. The figure shows the respective toll for PCs (left) and vans (right) in the risk-neutral case (NEUT, blue) and the risk-averse case (AVRS, red). Overlap is shown in purple.	176
Figure 6-7	Recommended price adjustments for local public transport. Prices of urban trains, metro/tram and public buses are entangled. The figure shows the risk-neutral case (NEUT, blue) and the risk-averse case (AVRS, red). Overlap is shown in purple.	178
Figure 6-8	Recommended price adjustments for long-distance trains (left) and coaches (right) in the risk-neutral case (NEUT, blue) and the risk-averse case (AVRS, red). Overlap is shown in purple.	178

List of Tables

Table 3-1	Travel surveys across Europe that served as data source to derive mode-specific Lorenz curves	68
Table 3-2	Fuel-specific well-to-tank (WTT) resource production share of emissions along with quality data ratings for uncertainty assessment. Error ranges: A \triangleq 10 to 30%, B \triangleq 20 to 60%, C \triangleq 50 to 200%, D \triangleq 100 to 300%, and E is an order of magnitude.	86
Table 3-3	Precision indicators of emission estimate for different vehicle categories (EEA, 2014b): A \triangleq statistically significant emission factors (EFs) based on sufficiently large set of measured/evaluated data; B \triangleq not significant, based on small set of data; C \triangleq estimated based on literature; D \triangleq estimated by similarity or extrapolation. E introduced to account for potential use of devices that may obfuscate real driving emissions of NO _x of diesel-fuelled vehicles under test conditions.	87
Table 3-4	Specific fuel consumption of different categories of locomotives.	89
Table 3-5	Annual average PM _{2.5} -to-PM ₁₀ ratio follows a right-skewed distribution with considerable variance. However, the variance can be explained partly by correlation to the station coordinates but seems to undergo temporal variation to a much lesser extent. This encourages use of a prediction model in other years than the period used to train a model (e.g. when conducting cross-validation by removing the year 2005 from the 13 years period).	92
Table 3-6	Datasets used to develop random forest model. Temporal coverage and spatial resolution refer to the data used to feed into the model. The population density was aggregated to 1 km ² to cover a more representative area.	93
Table 3-7	Relative risk (RR) and concentration-response functions (CRFs) for long-term exposure to PM, O ₃ and NO ₂ as recommended by (WHO, 2013a).	104

Table 3-8	All-cause background mortality per 100,000 people (Age-standardized death rate (SDR) calculated by World Health Organization (WHO) using standard European population structure.).	105
Table 3-9	Country- and pollutant-specific reduction in life expectancy in 10^{-3} YOLLs per $1 \mu\text{g}/\text{m}^3$ change in ambient concentration. Life-table calculation was applied for estimated age distribution in the year 2030.	109
Table 4-1	Query terms used for literature review. Bureau of Infrastructure, Transport and Regional Economics (BITRE) allows either a search for any of the words or of an exact phrase only, whereas TRIS and ITRD allow logical AND- and OR-operators.	122
Table 4-2	Coefficients of meta-regression model for short-term public transport demand cross-elasticity of fuel-price (for non-business purposes).	126
Table 4-3	Coefficients of meta-regression model for the logarithm of short-term urban car travel demand (non-business) and for short-term urban rail-bound transport demand cross-elasticity of bus fares (all purposes).	128
Table 4-4	Coefficients of meta-regression model for the logarithm of short-term car travel demand and for the logarithm of short-term bus travel demand cross-elasticity of rail-bound transport fares (all purposes).	133
Table 4-5	Coefficients of meta-regression model for the logarithm of short-term non-urban car travel demand of rail-bound transit fares (all purposes).	138
Table 5-1	Abatement cost of software modifications for Euro 5 and Euro 6 diesel-fuelled PCs and vans per 1,000 PKM. Underlying assumptions are given in the text. Numbers in brackets represent 95% CI levels.	148
Table 5-2	Reduction potential of software modifications for Euro 5 and Euro 6 diesel-fuelled PCs and vans in 2030.	148
Table 5-3	Abatement cost of BNOx-SCR system for Euro 5 and Euro 6 diesel-fuelled PCs and vans per 1,000 PKM. Underlying assumptions are given in the text. Numbers in brackets represent 95% CI levels.	150
Table 5-4	Reduction potential of BNOx-SCR system for Euro 5 and Euro 6 diesel-fuelled PCs and vans in 2030.	150

Table 5-5	Abatement cost of BNO _x -SCR system for Euro 5 and Euro 6 diesel-fuelled buses per 1,000 PKM. Underlying assumptions are given in the text. Numbers in brackets represent 95% CI levels.	153
Table 5-6	Cost of replacing an existing vehicle with a new Euro 6 real driving emissions (RDE)-conform diesel PC or van per 1,000 PKM. Underlying assumptions including a scrapping bonus reduction are given in the text. Numbers in brackets represent 95% CI levels.	155
Table 5-7	Reduction potential of diesel particle catalyst for pre-Euro 4 diesel-fuelled PCs and vans in 2030.	158
Table 5-8	Abatement cost of diesel particle catalyst for PCs and vans per 1,000 PKM. Underlying assumptions are given in the text. Numbers in brackets represent 95% CI levels.	158
Table 6-1	Summary of policies.	165
Table 6-2	Summary of technical abatement options.	166
Table 6-3	Overall net benefit [bn-€] for given NO _x reduction goals. 90% CIs are given in parentheses.	168
Table 6-4	Overall net benefit in billion Euros for given values of ϕ . 90% CIs are given in parentheses.	173
Table A-1	Model input disaggregation for regions (R).	189
Table A-2	Model input disaggregation for periods of the day (PD).	189
Table A-3	Model input disaggregation for countries (C) of the EU28+2 follows along ISO 3166-1 codes (UK used instead of GB).	190
Table A-4	Model input disaggregation for income (I) as proxy for socio-economic status.	191
Table A-5	Model input disaggregation for vehicle category (K).	191
Table A-6	Model input disaggregation for technology and fuel (T).	192

List of Acronyms

- AIC Akaike information criterion. 71
- ANN artificial neural network. 19, 20
- AOT accumulated ozone exposure over a threshold. 14
- AOT40 accumulated ozone exposure over a threshold of 40 ppb. 18, 20
- AQI Air Quality Index. 18, 20, 21
- ARA absolute risk aversion. 54
- BEEP best economic environmental pathway. 13
- BIC Bayesian information criterion. 71
- BITRE Bureau of Infrastructure, Transport and Regional Economics. xviii, 115, 118, 120
- BMA Bayesian model averaging. xi, 69, 70
- CAD central activity district. xv, 62, 162, 172, 173, 187
- CARA constant absolute risk aversion. 54
- CBA cost-benefit analysis. viii, 5, 6, 8, 9, 11, 20, 21, 32, 101, 182
- CBD central business district. 135
- CCZ congestion charge zone. 152
- CE Consumer Expenditure survey. 74
- CEA cost-effectiveness analysis. 6–8, 10, 11, 21
- CER cost-effectiveness ratio. 7, 8
- CF conformity factor. 144, 162, 165
- CI confidence interval. xiii, xix, 51, 101, 105, 166, 171

- CLRTAP Convention on Long-range Transboundary Air Pollution. 10, 12
- CNG compressed natural gas. xiv, 84, 168
- CO carbon monoxide. 74
- CO₂eq CO₂-equivalent. 40, 109–111
- CRA comparative risk assessment. 6, 7
- CRF concentration-response function. xvii, xxx, 42–45, 101, 102
- CRT continuously regenerating trap. 155
- CVaR conditional value-at-risk. 55, 56, 162, 170, 171
- DALY disability adjusted life year. 3, 7, 8
- DARA decreasing absolute risk aversion. 54
- DE deterministic equivalent. 161
- DOC diesel oxidation catalyst. 155
- DoE design of experiments. 19
- DPF diesel particulate filter. 143, 154, 155, 164
- DRF dose-response function. 22, 28
- DUH Deutsche Umwelthilfe e. V.. 147, 152
- EC European Commission. 100
- EEA European Environment Agency. 62, 80, 83, 86
- EF emission factor. xvii, 42, 61, 79, 80, 85
- EIA environmental impact assessment. 6, 7
- EMP Extended Mathematical Programming. 161
- EU28+2 European Union, Norway and Switzerland. xi, xix, 4, 24, 64, 188

- EV expected value. 56, 162, 170
- GA genetic algorithm. 15–17
- GAMS General Algebraic Modeling System. 161
- GDP gross domestic product. xiv, 24, 68, 114, 122–126, 130, 131, 136
- GHG greenhouse gas. 15, 16, 86, 110
- GSD geometric standard deviation. 20, 94, 108–110
- GWP global warming potential. 109, 110
- IAM integrated assessment modelling. vii, 4–6, 8, 9, 11, 12, 14, 16, 20, 21, 33, 159, 179
- IC information criterion. 71
- ICD-10 10th revision of the International Statistical Classification of Diseases and Related Health Problems. 106
- IEA International Energy Agency. 62
- IPA Impact Pathway Approach. 5, 20–22, 41, 61, 92, 182
- IPCC Intergovernmental Panel on Climate Change. 80, 109, 110
- ITRD International Transport Research Documentation. 116, 118
- LCA life-cycle analysis. 6, 7, 9
- LCI life-cycle inventory. 7
- LCIA life-cycle impact assessment. 7
- LEZ low-emission zone. xiv, 143, 151–153, 163–170, 172, 176
- LLE loss of life expectancy. 101, 105, 106, 108
- LPG liquefied petroleum gas. 79, 84, 85
- MCA multi-criteria analysis. 6, 8

- MCDA multi-criteria decision analysis. 6, 8
- MIP Mixed Integer Problem. 24, 35, 50, 51, 161
- MOP multi-objective programming. 8, 18
- MPT modern portfolio theory. 9, 52
- MRA meta-regression analysis. viii, 4, 24, 113, 114, 116, 122–124, 151, 179
- NEDC New European Driving Cycle. 143–145
- NFL No Free Lunch. 17
- NFR Nomenclature For Reporting. 86
- NLP Non-Linear Problem. 50
- NMVOC non-methane volatile organic compound. 13, 14, 83
- OECD Organisation for Economic Co-operation and Development. 74, 116, 118
- PC passenger car. xv, xviii, xix, 146–148, 153, 156, 160, 165, 166, 170, 172–174
- PEMS portable emissions measurement system. 144, 146, 147, 153
- PKM person-kilometre. xi, xviii, xix, 33, 35, 62, 63, 65, 66, 72, 74, 79, 80, 83, 87, 146–148, 150, 151, 153, 155, 156, 170, 172, 174
- PLA piece-wise linear approximation. 23, 25, 28, 35, 49, 50, 57, 161, 180
- PPP purchasing power parity. xiv, 68, 124–126, 131, 136
- RA risk assessment. 7
- RDE real driving emissions. xix, 83, 144–146, 150, 153, 166, 169
- RoH rule of a half. 35, 36, 38, 183
- RR relative risk. xvii, 45, 101, 102, 104–106
- RRA relative risk aversion. 54

- SCC social cost of carbon. 109
- SCR selective catalytic reduction. 143–145, 148, 149, 154, 156, 160, 164, 165
- SDR age-standardized death rate. xviii, 103
- SFC specific fuel consumption. 87
- SIA secondary inorganic aerosols. 14
- SOA secondary organic aerosols. 12
- SOMO35 maximum daily 8 hours running mean ozone concentration accumulated over a threshold of 35 ppb. 18, 20
- SOS special ordered set. 50, 51
- SP Stochastic Programming. 161
- SR source-receptor. 15, 19, 21, 44
- SUV sport utility vehicle. 153
- SWO social-welfare optimum. 166
-
- TCRP Transit Cooperative Research Program. 115
- TDM transportation demand management. 113, 116, 118
- TKM ton-kilometre. 79
- TRB Transport Research Board. 116, 118
- TRID Transport Research International Documentation. 116, 117
- TRIS Transportation Research Information Service. 116, 118
- TRL Transport Research Laboratory. 114
- TSAP Thematic Strategy on Air Pollution. 100
-
- UBA Umweltbundesamt. 83, 155

- ULEZ ultra-low emission zone. 152, 165
- UN United Nations. 62, 105, 123
- UNECE United Nations Economic Commission for Europe. 38
- US United States. 127, 128, 132, 136, 138
- UWM Uniform World Model. 21
- VaR value-at-risk. 55, 56
- VDA Verband der Automobilindustrie e. V.. 150
- VKM vehicle-kilometre. 62, 65, 75, 79, 83, 147, 150, 155
- VOC volatile organic compound. xiii, 10, 74, 98–100, 156
- VOLY value of a life year. 108
- VPF value of prevented fatality. 108
- VSL value of a statistical life. 108, 109
- VTPI Victoria Transport Policy Institute. 116
- VW Volkswagen. 145, 146, 149
- WHO World Health Organization. xviii, 3, 100, 103, 104, 106
- WLTC Worldwide-harmonized Light-vehicles Test Cycle. 144, 147
- WTP willingness-to-pay. 8, 40, 45
- WTT well-to-tank. xvii, 84, 86
- YOLL years of life lost. 7, 105, 106

List of Symbols

- $A_{K,M}$ Annuity cost of technological option M per unit of K
- $B_{K,T}$ Refers to behavioural adaptations induced by policy instruments
- C Country
- $D_{I,C}$ Amount of avoided damages caused by activities conducted by members of I in country C in the reference case
- E General income elasticity
- $G_{C,K,T}$ Average vehicle age of vehicles in country C of category K and technology T
- $G_{I,C,K}$ Weighted average vehicle age of vehicle in country C of category K in income group I
- $\Gamma_{\tau,\tau'}$ Assumed growth rate of per-capita income from τ to τ'
- I Income group
- $I_{K,T,P}^{(\gamma,P')}$ Annual rate of impact γ due to exposure to P'
- $\tilde{I}_{K,T,P}^{(\gamma,P')}$ Approximate annual rate of impact γ due to exposure to P' , i.e. approximation of $I_{K,T,P}^{(\gamma,P')}$
- K Category of activity, e.g. a vehicle type
- $L_{I,C}$ Reduction in additional utility that affects members of group I in country C
- $L_{C,K}$ Lorenz curve of transport mode K in country C
- $LE(x)$ Life expectancy at age x
- $L(r)$ The family of Lamé curves

- M Technical measure
- Ω Set of realisations of all stochastic parameters ($\Omega \subset \hat{\Omega}$)
- $\hat{\Omega}$ Totality of all possible realisations of all stochastic parameters ($\hat{\Omega} \supset \Omega$)
- P Pollutant
- PD Time period (e.g. peak or off-peak)
- $\Phi_{K,T,P}$ Monetized impact caused by the release of pollutant P per unit of activity of category K and technology T
- $\Phi_{K,T,P}$ Monetized environmental impact of conducting a unit of activity (K, T) for a given pollutant P
- $\Pi_{K,T,Q,K',T'}$ Indefinite integral of $\pi_{K,T,Q,K',T'}$
- $\tilde{\Pi}_{K,T,Q,K',T'}^{(j)}$ Value of $\Pi_{K,T,Q,K',T'}$ at interval index j
- Q Characteristic of an activity, e.g. its price
- $Q^{(p)}$ Set of cost components the public faces as opposed to Q representing characteristics an individual is concerned with like private cost components
- R Region (e.g. urban or non-urban)
- $S_{I,C}$ Total economic cost to be spent by society to support policy intervention affecting members of group I in country C
- $S(x, x')$ Survival function: fraction of a cohort of age x that survives until age x' or beyond
- T Technology type within a category K
- $T_{K,T}$ Represents technological adaptations due to policy regulations

-
- Z Objective function representing the net benefit for society
- $a_{K,T}$ Variable level of activity conducted within category K by technology T
- $\hat{a}_{K,T}$ Fixed initial reference level of activity conducted within category K by technology T
- $c_{P'}$ Change in concentration of pollutant P'
- $\tilde{c}_{P,P'}^{R,\tilde{r}}$ Approximate unit change in concentration of pollutant P' at receptor \tilde{r} due to unit emission change of precursor P originating in source region R
- $\delta(\mathbf{r})$ Density of the receptor at location \mathbf{r}
- $e_{K,T,P}$ Total emission of P released due to activity of (K, T)
- $e_{R,K,T,P}$ Total emission of precursor P released due to activity of (K, T) in region R
- $\eta_{K,Q,K'}$ Cross-elasticity of demand of K' with respect to component Q of K
- $\eta_{I,C,K,Q,K'}$ Cross-elasticity of demand of K' with respect to component Q of K specific to income group I in country C
- $\hat{\eta}_{C,K,Q,K'}$ Meta-regressed cross-elasticity of demand of K' with respect to component Q of K specific to country C
- $f_{K,T,P}$ Emission factor of (K, T) with respect to pollutant P , i.e. the amount released per unit of activity of K
- $g_{C,K}$ Regression coefficient for the estimated Lorenz curve of transport mode K in country C
- $k_{C,K}$ Regression coefficient for the estimated Lorenz curve of transport mode K in country C
- $\kappa_{M,I}$ Investment cost of measure M at the beginning of implementation

- $\kappa_{M,O}$ Operational cost of measure M per year
- λ Vector of the independent variables representing degrees of implementation of technical options in the piecewise-linear approximated formulation
- $\lambda_{K,Q}^{(j)}$ Independent variable and vector element of λ
- $m^{(\gamma,P')}$ Slope of the respective CRF
- $\mu(x')$ Mortality rate, s.t. someone who has reached age x' has a probability $\mu(x')\Delta x'$ of dying between age x' and $x' + \Delta x'$
- n_M Estimated period of application of measure M in years
- ω Single realisation of all stochastic parameters ($\omega \in \hat{\Omega}$)
- $\phi_{\gamma,\tau}$ Monetary value of one unit (or case) of γ at time τ
- $\pi_{K,T,Q,K',T'}$ Shift from a demand served by (K,T) to (K',T') induced by a change in characteristic Q
- $\pi_{K',T',Q,K,T}$ Shift from a demand served by (K',T') to (K,T) induced by a change in characteristic Q
- $\tilde{\pi}_{K,T,Q,K',T'}^{(j)}$ Value of $\pi_{K,T,Q,K',T'}$ at interval index j
- \mathbf{r} Location of a receptor
- r Discount rate
- \tilde{r} Approximate location of the receptor location \mathbf{r}
- $s_{K,T,Q,K',T'}$ Additional non-private spendings needed to cover responses to Q , i.e. to be able to serve demand by category K' and technology T' which was previously served by category K and technology T
- $t_{K,T}$ Share of technology T within category K

-
- τ Income or wealth
- $\tau_{I,C}$ Cumulative share of total income for income group I
- $\hat{\tau}_C$ Median income in country C
- $\tilde{\tau}_{I,C}$ Relative income share of income group I in country C
- $u_{K,T,Q,K',T'}$ Utility lost when serving a given demand by category K' and technology T' which was previously served by category K and technology T due to change in Q
- \mathbf{x} Vector of the independent variables representing degrees of implementation of technical options in the non-linear formulation
- $x_{K,Q}$ Vector element of \mathbf{x} and the variable level of price component Q of category K
- $\hat{x}_{K,Q}$ Fixed initial reference level of price component Q of category K
- \mathbf{x}^* Variant of \mathbf{x} with isolated price change while all other prices remain at the reference level
- $\tilde{x}_{K,Q}^{(j)}$ Sampling point of $x_{K,Q}$ at interval index j
- ζ Vector of the independent variables representing degrees of adaptation through behavioural response to policies
- $\zeta_{K,T,M,T'}$ Shift from a demand previously served by category K and technology T to T' of the same category due to technological option M becoming available

Part I

Background and methodology

1 Introduction and contributions

1.1 Motivation

Exposure to ambient particulate matter is one of the 10 leading risk factors globally, causing about three times as many disability adjusted life years (DALYs) as drug use and about half the DALYs caused by the combined effect of tobacco smoking and exposure to second-hand tobacco smoke (Murray and Lopez, 2013). While this covers exposure to particles only, the World Health Organization (WHO) recently quantified the relative risk of mortality due to exposure to nitrogen dioxide (NO₂) in ambient air at a similar level as that of particulate matter (WHO, 2013b). Thus, the importance of establishing further policies to improve air quality levels along with reducing negative climate change impacts can hardly be overemphasized. Although policy-makers made progress in generally reducing levels of air pollution in Europe over the past decades, target values in many places, especially in densely populated urban areas, remain to be not met. The transport sector is an important contributor to air pollution: In 2009, 58% of nitrogen oxides (NO_x) released in the European Economic Area are direct emissions attributed to this sector. More than half of it are exhaust emissions from on-road transport activities, especially from diesel-fuelled vehicles. Every fourth ton of fine particles (PM_{2.5}) is a result of transport activities and about half of these emissions are caused by on-road transport (EEA, 2009).

Recent disclosure of wide-spread application of so-called defeat devices, which are suspected to undermine emission standards of NO_x, is likely to have reduced the general public's trust in policy making with respect to pursuing future compliance with air quality limits. This is a severe issue especially in urban areas where people experience high levels of exposure to nitrogen dioxide and to fine particles of which NO_x is an important precursor.

Therefore, policy-makers are urged to find effective and efficient strategies to overcome these problems. The efficacy of policies is difficult to measure. Thus, there has been a long history of computer-based policy support tools to aid decision-makers to estimate

policy effects and determine such strategies. Most of these tools looked at the effect of policies in a deterministic manner. However, processes in nature seldom can be resembled as a deterministic scheme or system. Stochasticity is an inherent part of environmental modelling as there is variability in almost all environmental factors and there are obvious limits to observe them. Similarly, human behaviour and response to policy can be characterized as inherently uncertain and thus is far from deterministic. It is surprising that dealing properly with the sources of uncertainty in the estimation of environmental pollution and people's stochastic response to policy have received relatively little attention in scientific literature. This work aims to contribute to overcome this issue. Therefore, a model was developed to represent policy implementation and peoples' response as well as the resulting change in pollution and utility. The model was extended to a stochastic optimization approach that is able to consistently reflect a decision-maker's risk attitude when selecting policies for abatement strategies.

Passenger transport is considered a representative example for sectors in which considerable technical progress has already been achieved. This calls for policy-induced change of travel behaviour whereas current integrated assessment modelling (IAM) approaches ignore this and focus on technical options only. Thus, an extensive meta-regression analysis (MRA) of transport elasticities was carried out to enable provision of probabilistic meta-regression models of people's response to intervention. In the context of transport elasticities few work so far has dealt with the transferability of empirical findings to different contexts. It is shown in this thesis that travel behaviour is significantly correlated with the wealth of a country, its population density and the quality of alternative transport modes. Thus, meta-regression models are proposed to enable transferability of literature findings into different contexts. The use of such approaches is strongly encouraged over simple application of existing evidence which may have been determined in different contexts, say during different time periods or in different countries.

The stochastic model was applied in the context of passenger transport in the member states of the European Union, Norway and Switzerland (EU28+2). The model is allowed to choose from a set of policies during policy instrumentation. It operates with flexibility in terms of adjusting price components of several transport modes and simultaneously is allowed to select from a pool of technical options. By conducting several sensitivity anal-

yses of the level of risk-aversion, trajectories of cost-efficient strategies were determined under several nuances of risk-aversion ranging from a neutral stance to risk-aversion. Additionally, the effects of NO_x reduction goals were investigated and the sensitivity of the outcome with respect to risk attitudes was analysed. This allows to assess the robustness of policy recommendations derived from the model presented in this thesis.

1.2 Objectives

In this chapter the main objectives of this thesis are presented. Limitations of existing work are linked to these objectives. They are described in chapter 1.4. The contributions of the approach developed in this thesis are also obviously tied to these objectives and are presented in chapter 1.5.

It is well-known that individuals show different reaction to risk and uncertainty because they tend to value probabilities of losses and gains differently (cf. [Tversky and Kahneman \(1992\)](#)). However, this behaviour is not properly addressed in existing work on IAM: Existing approaches either rely on expected values – or even best guesses –, exclude assessment of uncertainties entirely or recommend so-called 'no regret' strategies. The latter deals with uncertainty by simply overestimating potential cost (cf. GAINS, chapter 1.4.1). A detailed analysis of the shortcomings of current approaches is presented in chapter 1.4.

Obviously, such approaches inhibit proper decision-making, especially under a risk-averse stance. Thus, a novel optimization scheme is needed that is able to show the benefits and losses for different levels of a risk-aversion. Hence, the first objective of this thesis is as follows:

O1: Enable decision-makers to determine cost-efficient outcomes under different levels of risk aversion. This calls for a cost-benefit analysis (CBA) approach to determine cost-efficient policies. Other potential methodologies for impact assessment are discussed in chapter 1.3. In addition, consistent determination of uncertainty of impacts along the full chain of the Impact Pathway Approach (IPA) is mandatory. Furthermore, uncertainty of reaction to policy needs to be properly accounted for. On top of this,

uncertainty needs to be incorporated into an optimization scheme as it may influence policy selection. Specific risk attitudes of a decision-maker need to be represented in a modelling framework. As an individual's level of risk aversion is difficult to address, a sensitivity analysis of the impact of different levels of risk aversion on policy selection is mandatory.

Secondly, current work on IAM suffers from solely focusing on technical options while widely ignoring behavioural change. Non-technical measures are more complex to represent in a mathematical framework than technical options and the effects of related policies are naturally difficult to quantify. Consequently, the second objective of this thesis follows along these lines:

O2: Enable decision-makers to conduct a conjoint assessment of policies inducing behavioural change along with considering technical options. The impact of technical options has been the main focus of IAM approaches (cf. chapter 1.4). Non-technical measures need to be properly represented in a mathematical modelling framework. Furthermore, a thorough literature review has to be conducted to determine people's response to certain policies. More specifically, it is necessary to describe and quantify the behavioural change (e.g. change in individual transport demand) in response to the implementation of a specific policy instrument affecting a certain characteristic of an activity (e.g. price components like tolls or taxes on fuel). Behavioural responses usually come in the shape of changing demand. It is well known that behavioural response – often quantified by elasticities – is non-linear. Consequently, the optimization approach has to be able to deal with these non-linearities.

1.3 Background on assessment methodologies

Several kinds of assessment methodologies and decision making procedures are discussed in the context of effective or efficient environmental protection strategies. The most prominent ones are comparative risk assessment (CRA), cost-effectiveness analysis (CEA), CBA, and multi-criteria analysis (MCA) (sometimes referred to as multi-criteria decision analysis (MCDA)). When these methodologies are applied they are commonly informed by life-cycle analysis (LCA) and environmental impact assessment (EIA) which are not

designed as stand-alone decision making tools on their own. Some of the methodologies deal with single or multiple indicators whereas some deal with costs in monetary terms, sometimes as a single indicator. In the following section the specifics of these methodologies will be discussed.

EIA is concerned with positive or negative consequences associated with a certain project. Usually, EIA ignores non-environmental impacts. It may not account for impact variation over time and its discounting. It cannot be applied as a decision making procedure as there is no decision rule. However, EIA is considered an important tool to determine essential inputs to other methodologies by assessing the impacts of environmental pollution in the first place.

Life-cycle impact assessment (LCIA) performs an LCA and, hence, looks at life-course impacts of certain projects and their alternatives. Therefore, it considers additional information, not only the direct impacts of a classical EIA. Again, there is no obvious decision rule to base planning decisions on: Often neither investment cost nor any other non-environmental cost are considered. The outcome, e.g. per-unit values, is often provided by access to a life-cycle inventory (LCI) which makes it useful as input to further assessment. Sometimes, the environmental impacts (from EIA) or the whole life-cycle impacts (from LCIA) are used as the criterion in a CEA or CRA.

CRA performs risk assessment (RA) for several options, i.e. projects, policies or similar. In an environmental context, RA is the assessment of environmental or health risk associated to a certain policy or project. This is, for instance, the chance of a defined health effect occurring in a member of a certain defined population, e.g. mortality in the most drastic case. The aim of CRA is to normalize the effects across the options to make them, as the name suggests, comparable. When monetary factors are added to it, CRA becomes similar to CEA. The latter usually deals with benefits. Note, however, that CRA deals with risks which essentially is a different concept.

CEA uses a single indicator, namely effectiveness, and builds the ratio of effects and costs as a non-monetary indicator. This yields the effect achieved per cost unit. The indicator may for instance be years of life lost (YOLL) or DALYs as a unit to measure health effects in terms of reduced or impaired duration of life. For the latter example the so called cost-effectiveness ratio (CER) is given in avoided DALYs per money spent. The

basic idea is to rank a number of policies based on their CER to indicate which of the policies yields larger impact per money spent. However, an interesting question cannot be answered with this methodology, namely as to whether *any* of the options actually should be chosen at all, and consequently the money should be spent on it at all. From an ordinary ranking one may not immediately derive this decision because the unit of the indicator – the desired effect – is not given in monetary terms. So it is not obvious whether an option is worth pursuing. Matters are even worse when different indicators are used across several CEA. The effectiveness measure, i.e. the indicator in the analysis, has to be chosen beforehand and it is often an informed expert's choice, like a DALY or similar.

It is possible to determine monetary values for the effects: This is the case if the metric is an individual's preference expressed or revealed as his or her willingness-to-pay (WTP) with respect to avoiding a specific outcome. Applying IAM one attempts to assess the effects of policies in a multi-disciplinary process in which the individual assessment procedures are non-trivial. When the effect is given in monetary terms one ends up conducting a CBA in which one is able to trade off benefits against losses in monetary terms.

When introducing multiple indicators of potentially different measures of effectiveness (at least one of them non-monetary) one can apply MCA instead of CBA. The indicators are often called attributes or criteria and often they are selected by policy-makers or decision-makers. The objective of the policy decision is defined based on these attributes as opposed to a single objective of cost-efficiency used in CBA.

The level of achievement of the individuals attributes is measured in scores. Their relative importance can be set by attaching weights to them. Simple MCA calculates the average weighted score as the final outcome. A vast body of literature exists that deals with solving more sophisticated forms of multi-objective programming (MOP) problems under constraints.

When building a ratio similar to the CER in CEA, also MCA suffers from not being able to tell whether a policy is worth adopting at all. This is a considerable drawback compared to CBA. The results of CEA and MCA are only efficient for predefined given investment cost but both do not allow a scenario in which none of the defined policies should be implemented at all. MCA, however, yields the same results as CBA when the

following is met: (i) The scores of MCA and CBA are the same, and (ii) weights of MCA correspond to CBA shadow prices and the weight on cost is unity. General pros and cons of MCDA are elaborated in [Diakoulaki and Grafakos \(2004\)](#). Within the context of externalities, MCDA was successfully applied in the NEEDS project ([Bachmann, 2013](#)). The general welfare economic approach is described in [Bachmann \(2011\)](#).

In this thesis, a cost-benefit optimization approach is developed which incorporates results of an LCA. The objective of the approach to maximize net benefit is in line with the welfare economic approach to correct market failures.

1.4 Related work

There is a vast body of literature dealing with handling risk or uncertainty in decision making and other approaches to generally quantify the impacts of uncertainty and risk. These are briefly described in chapter 2.5.1 along with other prominent related concepts like modern portfolio theory (MPT).

Another common concept utilized in this thesis is elasticities of demand, in particular cross-elasticities of demand in the European transport sector. Again, there is an extensive body of literature that investigates effects of intervention on transport demand. A summary is given in chapter 4.1.

This chapter presents work that is more closely related to the objectives of this thesis. The focus is on other existing approaches dealing with IAM in the context of air pollution and climate impacts. Approach descriptions are provided and their limitations with respect to meeting the objectives of this thesis are laid out. Subsequently, in chapter 1.5, it is presented how the work developed in this thesis aims to meet the objectives and the specific contributions are summarized.

1.4.1 GAINS

Approach description The GAINS model ([Kiesewetter et al., 2015b](#); [Amann et al., 2011](#); [Wagner et al., 2007](#)) explores control strategies that aim to improve air quality

and reduce emissions of greenhouse gases simultaneously. It was preceded by the single-pollutant model RAINS (Alcamo et al., 1990; Amann et al., 2004). The model is applied in policy analysis to assess potential outlooks on likely developments of air quality under different control strategies within over 40 countries in Europe.

Using reduced forms of complex models the impact from emission over dispersion to impacts are described in functional forms (Amann et al., 2011). Using a matrix coefficient-based approach dispersion as well as impacts are assessed as linear combinations of emission reductions.

In the most recent implementation health impacts are assessed on a 7 by 7 km² grid (Kiesewetter and Amann, 2014). However, some down-scaling schemes for urban areas across Europe have been developed which enable to address urban background levels of NO₂ (or NO_x) and PM₁₀ plus roadside concentrations of NO₂ and PM₁₀ (cf. Kiesewetter et al. (2015a, 2013)). Also, urban PM_{2.5} levels can be estimated (Kiesewetter et al., 2014).

The objective of the optimization module is to meet user-defined target levels at least cost. Therefore, GAINS assesses emission control measures across countries, sectors and pollutants. The optimization routine selects from a collection of 3,500 pollutant-specific technical measures for reducing SO₂, NO_x, volatile organic compound (VOCs), NH₃, PM_{2.5}, CO₂, CH₄, N₂O and F-gases. Costs of the technical options are assessed using cost curves to determine the marginal cost of emission control (Amann et al., 2011).

Country-specific versions of the GAINS model are widely used by decision-makers throughout the EU to address air quality issues and are used in various working groups of the Convention on Long-range Transboundary Air Pollution (CLRTAP). Furthermore, the model has been applied in regions with high levels of air pollution, like India and China. GAINS is well-established in the scientific community.

Limitations There are several limitations in the general implementation that will be shortly addressed in the following paragraphs. The major disadvantages result from the lack of assessment of non-technical measures and the ignorance of uncertainties during measure selection. GAINS conducts a CEA only and uses cost curves for investment decisions which leads to further shortcomings in the assessment. In chapter 1.5 it will be

pointed out how the approach proposed in this thesis overcomes these issues. The most important limitations of GAINS with respect to the objectives of this thesis are:

1. The problem formulation and objective function of GAINS are given in a way that the approach finds the least-cost scenario which fulfils user-defined target levels. In this context, cost only refers to implementation cost of emission control options. Thereby, GAINS does not look for cost-efficient solutions but instead only conducts a CEA, not assessing the monetary value of benefits and avoided impacts. It is explained in chapter 1.3 why CBA is superior in addressing the aim of social welfare maximization postulated by environmental economics.
2. Costs in the model refer to implementation cost of technical options. These are assessed by determining abatement cost curves upfront. Single abatement cost curves have been used in IAM for a long time, serving as input to optimization problem formulation as in GAINS. However, they have obvious limitations when used in a complex setting as the one at hand. In fact, the limitation of abatement cost curves in the presence of interdependencies are severe: In a multi-pollutant and multi-effect context, there are interdependencies between the effects or impacts when the emission amount of a multiple precursors are reduced. [Reis et al. \(2005\)](#) point out that generating abatement cost curves as input to optimization leads to an artificial constraint as abatement options have to be ranked, for instance according to their unit cost. By applying such approach, it is impossible to account for interdependencies of options, e.g. in terms of varying mitigation efficiency of a specific option when being conjointly applied with other options due to potential mutual influence.
3. The limitation described above becomes even more important when dealing not only with technical measures but also non-technical options. The latter affect the behaviour of people and, hence, the level of activity attributed to a certain source. GAINS does not address the assessment of behavioural change endogenously nor does it cover structural changes in the agricultural sector or the energy system ([Amann et al., 2011](#)). The only way to assess change in future human behaviour in GAINS to a limited extent is to separately optimize exogenous scenarios which, individually, reflect this change. The driving forces of emission, e.g. certain demands

resulting in human activities, cannot be included in the optimization process and, hence, cannot be adjusted by policies within GAINS. With increasing technical advances in many economic sectors the need for properly assessing policies that induce behavioural change is immanent. As mentioned before this is in particular the case for any integrated assessment undertaken in the transport sector.

4. As with any other IAM approach there is substantial uncertainty in the assessment of impacts and costs (cf. [Kiesewetter et al. \(2013\)](#); [Amann et al. \(2011\)](#)). [Schöpp et al. \(2005\)](#) assessed uncertainty propagation through the model framework of RAINS. However, [Amann et al. \(2011\)](#) states that it was found difficult to identify uncertainties of input parameters in the first place and concludes that this inhibits robust quantification of full uncertainties of the GAINS model. As a consequence, GAINS focuses on a so-called no-regret approach by avoiding regret investments and/or the so-called precautionary approach by avoiding the risk of serious damage. This is achieved, for instance, by deliberately over-estimating control costs and by excluding uncertain assessment of particles forming from uncertain chemical processes, e.g. the formation of secondary organic aerosols (SOA) (cf. [Amann et al. \(2011\)](#)). The authors admit that the model results are, thus, clearly biased. As a result, the analysis of separate exogenous scenarios and their individual optimization result is the only way to assess uncertainties in that sense. The optimization scheme itself is purely deterministic. There is no endogenous treatment of uncertainties. Therefore, proper quantitative analysis of risks of policy decisions as laid out in the objectives of this thesis is not possible within the optimization framework of GAINS. It has to be highlighted though, that the modelling team publicly provides all input data and discusses development within working groups of the CLRTAP to facilitate legitimacy of the results.

1.4.2 OMEGA-2 and OMEGA-O₃

During the 1990s and early 2000s, assessment models were addressing air pollution in a comparably simple manner. They focused on acid rain and acidification when putting their analysis efforts on reduction of single pollutants, mainly SO₂ and NO_x. Conveniently, the estimated decline in deposition due to reduction of emissions of either of the

two pollutants, i.e. the assessed impacts of policies, usually were of the same order of magnitude thereby considerably simplifying the analysis (Reis et al., 2005). When the scientific focus shifted towards ground-level ozone, the modelling efforts were inclined to become more sophisticated by incorporating non-linearity as well as source locations (cf. Friedrich and Reis (2000) in Reis et al. (2005)).

To cope with these issues, iterative approaches have been developed as an alternative to established, often linear, optimization methods. One of the underlying rationales was to incorporate non-linearity to a limited extent and to maintain transparency by making model outcomes straightforward to interpret by both scientists and decision-makers. A simple step-wise approach to determine economically and environmentally effective emission reductions, the so-called best economic environmental pathway (BEEP), has been developed by ApSimon et al. (1994). This was the first of such approaches. A more sophisticated general methodology for iterative optimization approaches in the context of air pollution control has first been formulated by Simpson and Eliassen (1997) (cf. Reis (2005)). However, it is well-known that iterative models sometimes converge too quickly towards a local optimum or even non-optimal points in the solution space. Some strategies have been proposed aiming to avoid or reduce these undesired effects. A prominent case has been made during the development of the OMEGA-O₃ model (Reis et al., 2001; Friedrich and Reis, 2000) developed during the INFOS research project, and its fundamentally different successor OMEGA-2 (Reis and Nitter, 2008; Reis et al., 2005) developed during the MERLIN research project. The innovative aspects and limitations of both will be discussed in the following sections.

Approach description The OMEGA-O₃ model supports the development of cost-effective air pollution abatement strategies focusing on ground-level ozone. The focus is on ozone precursor substances, i.e. mainly NO_x and non-methane volatile organic compound (NMVOCs) and to some extent on carbon monoxide. A major problem when designing strategies aiming at reduction of tropospheric ozone is the non-linear relationship of precursors in the formation of ozone and the treatment of nitrogen oxide emissions. The latter play a role in both ground-level ozone formation and acidification. The effects of potential NO_x reduction measures on either of both may be quite different across countries in Europe. Also, reduction of other precursors, namely NMVOCs, may be more cost-

effective towards reduction of ozone levels (Reis et al., 2001). This particular problem may seem specific to ozone formation, however the issue also affects other pollutants; for instance, secondary inorganic aerosols (SIA) formation due to the formation of ammonium nitrate involving precursor emissions of NH_3 and NO_x .

The optimization procedure of OMEGA- O_3 follows the abatement cost curve of each of 15 European countries and for each precursor pollutant. It aims to determine the least-cost option to achieve predefined target levels. In each step of the iteration, the emissions of a country are reduced by a small amount. The changes in impact due to the emission reduction are determined using the EcoSense model (Krewitt et al., 1998). The cost is determined by the position on the abatement cost curve. Subsequently, the change in pollution, here the delta in accumulated ozone exposure over a threshold (AOT), is assessed representing the benefits gained. For each option, the cost-effectiveness, corresponding to the ratio of the change in AOT per cost, is determined. Obviously, the option with best ratio per country and pollutant is selected. After reducing the emissions, changed ozone concentration levels are compared to the predefined target levels representing the break criteria of the loop iterations to decide whether to continue with the step-wise approach.

While the approach results in an optimal solution with respect to the model formulation, the utilization of cost curves involves the weaknesses already mentioned. This cannot be avoided when using cost curves specific to single pollutants. In the case of options that reduce multiple precursors, i.e. both NO_x and NMVOC emissions in the case of tropospheric ozone, Reis et al. (2001) proposed to allocate cost proportions to precursors. Obviously, this does not solve the issue of properly integrating multiple pollutants – and also multiple effects – in IAM. Hence, Reis et al. (2005) proposed a fundamentally different approach to avoid the use of single-pollutant cost curves compiled outside of the model as used by GAINS and OMEGA- O_3 . The approach was implemented in the OMEGA-2 model in the scope of the MERLIN project. The model avoids ranking of options and measures based on their cost-effectiveness and, consequently, does not rely on cost curves. As another innovation, the OMEGA-2 allows both technical and non-technical options to be selected during the optimisation. Within the model technical measures are considered as the ones affecting supply. Non-technical measures are defined as affecting the end-user demand (cf. UCL (2004), Reis et al. (2001)). This is different from the traditional

definition of technical measures affecting emission factors, therefore sometimes referred to as end-of-pipe measures, and non-technical measures affecting activity levels.

OMEGA-2 applies a measure-matrix approach to reproduce interdependencies between pollutants and effects. The procedure relies on three datasets, namely (i) stock of activities, e.g. number of vehicles and their annual mileage, (ii) data on measures with respect to their applicability, costs, degree of implementation and efficiency, and (iii) further information on relationships between measures. Opposed to the previously proposed attempt to split cost data into single-pollutant abatement cost curves, the model – in a randomized fashion – applies and evaluates options relative to its application on stock, thereby better resembling real-world implementation of measures and their cost characteristics. Apart from allowing structural change by adjusting activity levels, the approach also achieves that measures affecting the emission of multiple pollutants at a time are no longer subject to artificial modelling constraints as has been the case before.

The objective of the approach is to select from all possible abatement options the set of measures which fulfils predefined air quality limit values and predefined emission limits on greenhouse gases (GHGs). While being a straightforward formulation in terms of objective function and decision variables, the search for an optimal solution is seriously inhibited by the sheer amount of possible combinations of measure application.

To address this obvious limitation, [Reis et al. \(2005\)](#) proposes the application of a meta-heuristic. The authors developed a tailored genetic algorithm which is a common approach used in optimization problems having to deal with a vast solution space. The approach starts with a randomly chosen population of strategies and proceeds in an iterative manner. First, it determines the changes in emissions per country and calculates the respective changes of concentration using source-receptor (SR) matrices from EcoSense ([Krewitt et al., 1998](#)) on a 50 by 50 km² grid. The strategies are then assessed with respect to the target criteria of air quality and GHG limits. Every genetic algorithm (GA) to a large extent relies on the proper evaluation of population members (here: the strategies) based on their so-called fitness, a selection step and subsequent application of so-called genetic operators. The fitness function in evolutionary algorithms is a particular form of an objective function. After evaluation, the 'worst' candidates are dropped. From the remaining strategies, the 'best' strategies are kept and some are recombined using the

cross-over operator. Some of the remaining strategies are copied in a subsequent population which is used in the next iteration. Termination is reached when the stop criterion is met which is represented by the compliance to air quality and GHG targets. While there are already many degrees of freedom, i.e. options for parametrisation, in GAs with respect to the fitness evaluation and candidate selection, particular attention has to be focused on the application of a combination of the two most prominent genetic operators, namely recombination (or cross-over) and mutation as the strategies chosen have considerable impact on the quality of the result. The operators produce a child strategy from a selection of a pair of parent strategies to build the population for the next iteration. In OMEGA-2, the offspring is formed by a 2-point cross-over by cutting two strategies into pieces to recombine them. Obviously, the proper genetic representation and the position of measures within a strategy plays an important role as the cross-over step may reduce diversity of a strategy with respect to impacts. To avoid unfortunate cuts in which the resulting two child strategies are not diverse but, for instance, overly focus on a particular pollutant the approach maintains variation by building groups of measures within a strategy that have similar effects. This is an attempt to make the offspring more diverse. As is the case with heuristics, such parametrizations intend to guide the search within the solution space but are no guarantee for convergence towards an optimum, neither local nor global.

Limitations OMEGA-2 overcomes the use of abatement cost curves which was a shortcoming of OMEGA-O₃ and any preceding IAM in the field of air pollution control at that time. While valuing the innovativeness of the approach taken by the OMEGA-2 model the major shortcomings of using a GA to deal with optimization problems are discussed in the following section. In summary, the approach suffers from its tendency to get trapped in a local optimum as opposed to finding the global. The approaches taken cannot provide bounds on the optimality of the results. Additionally, uncertainty is not addressed at all. The detailed shortcomings with respect to the objectives of this thesis are as follows:

1. Heuristics in general, and GAs in particular, are aimed at coping with huge search spaces but cannot provide any mathematical guarantee of global optimality of the result when dealing with non-trivial problems. The gain of quickly finding candidate solutions comes at the price of relinquishing mathematical rigorousness. Usually,

there is no way to compare the approximation provided by GA approaches with the best possible result for it being unknown. Thus, obviously, it is also impossible to determine the level of deviation from it as a hint of the quality of the approximation.

2. GAs are, in general, sensitive to the structure and characteristics of the initial solution. This results in difficult convergence properties. It is well-known that GAs may converge too fast towards local optima or even random solutions. While the design of GAs aims to find a short-cut to a 'good' candidate solution but not necessarily an optimal one, it does not reduce the complexity of the problem. The well-established No Free Lunch (NFL) theorem states that the computational cost of determining a solution is the same across search and optimization methods (cf. [Wolpert and Macready \(1997\)](#)). It is worth noting that OMEGA-2 aims at coping with these difficulties by starting off with a simulated annealing approach before applying the tailored GA approach. Also, OMEGA-2 aims to increase diversity in the selection operation via parametrization; however, the efficacy of these attempts cannot be properly measured.
3. Often, the aforementioned shortcomings of GAs are dealt with by tuning the specific parametrization of the tailored approach. For instance, the stop criterion of the iterative approach or the selection and mutation methods. These efforts have in common to aim at directing the search in solution space towards areas which are believed to be more likely containing local or global optima. OMEGA-2 does so by adjusting the genetic representation of the strategies in a certain format, by fostering local search, and by adjusting the genetic operators (cf. [Reis et al. \(2005\)](#)). However, these are to some extent arbitrary approaches that may find 'better' candidates under specific circumstances but, due to the aforementioned limitations, are unable to guarantee optimality nor can they provide bounds on the approximation.
4. By no means does the approach cope with uncertainty in the estimation of benefits and cost of candidate strategies. Within OMEGA-2, stochasticity is only present when randomly selecting candidate solutions from the population and to randomly recombine parent strategies. However, uncertainty is only involved with respect to the optimality characteristic of the outcome but not when utilizing input parameters or assessing outcomes. There is no assessment of uncertainty of the impacts

and costs involved and, hence, no assessment of the risk of decisions based on the outcomes can be conducted by policy-makers. Also, no precautionary efforts are made (as in GAINS) and no options to select no-regret strategies are provided.

1.4.3 RIAT

Approach description With focus on supporting environmental authorities to plan air quality control policies at regional level, namely in the Lombardy region of Northern Italy, the RIAT model applies an approach which at its core solves a MOP (Carnevale et al., 2012b, 2008; Pisoni et al., 2009). RIAT makes use of the technical options provided by the GAINS model and utilizes unit values to represent cost. Thereby, the approach inherits the limitations with respect to utilizing abatement cost curves. Also, the model can only assess technical options as it relies solely on the measures database provided by GAINS. The decision problem in RIAT is to determine the portfolio of technical options that leads to staying within the limit values of given pollutant-specific Air Quality Indices (AQIs) at least cost. According to Carnevale et al. (2012b), the optimization module uses functions provided by MATLAB. The model presents the entire set of efficient strategies, i.e. the Pareto frontier of solutions. The decision variables for the optimization approach are the application rates (or penetration levels) of the technical options. Therefore, the MOP balances two objectives, namely the air quality objective and the cost objective. RIAT searches for a cost-effective solution only as the air quality objective does not cover the impacts of pollution but deals with some predefined target levels of pollution concentration only. The air quality objective can be defined by the decision-maker as one of the following four indices: annual mean PM_{10} concentration, annual mean $PM_{2.5}$ concentration, the maximum daily 8 hours running mean ozone concentration accumulated over a threshold of 35 ppb (SOMO35) as a signal for human health impacts, and the accumulated ozone exposure over a threshold of 40 ppb (AOT40) as an indicator of impacts on vegetation. A common approach in RIAT is to apply a weighting scheme of relative importance of the individual AQIs by using a linear combination of the pollutant-specific AQIs as its first objective (Carnevale et al., 2012b). At the same time the model aims to minimize the cost of implementation for these options which is its second objective. Without being specifically mentioned, meeting the individual AQI targets can be

considered individual objectives.

RIAT uses a $6 \times 6 \text{ km}^2$ grid over the Lombardy region of Northern Italy. It is not unlikely that the model could be applied in other countries or regions as well, however, no references have been found that mention the RIAT approach being applied in another geographical domain. The source-receptor relationship utilized in RIAT is, to some extent, able of taking account of non-linearity in the dispersion and transformation of air pollutants. Therefore, RIAT uses a surrogate of the atmospheric model TCAM (Carnevale et al., 2012a, 2009, 2008). Commonly, SR matrices are determined by reducing precursor emissions individually in a predefined range (e.g. minus 15% relative to a base scenario) in each country. This has, for instance, already been applied in the NEEDS project and yields a large number of scenarios if the reductions of many precursors in several countries have to be assessed separately. Obviously, this renders the process of constructing SR matrices a computationally intensive task. However, by applying design of experiments (DoE) techniques the number of such precursor reduction scenarios can be lessened. Factor separation approaches using this technique have been proposed to achieve scenario reduction (Gabusi et al., 2008). Carnevale et al. (2009) and Pisoni et al. (2009) found that only a small number of scenarios is necessary to properly train artificial neural networks (ANNs) which hold source-receptor relationships for the Lombardy region. To achieve better results when comparing the outcome of ANNs to the full-scale atmospheric model, the approach was tailored to the region of Northern Italy in which total emissions originating from certain regional quadrants were considered as inputs. Thus, the approach had to be improved by integrating specific domain knowledge in the definition of the non-linear model structure (Carnevale et al., 2012a). The source-receptor approach has later been improved by Clappier et al. (2015).

Limitations The innovative aspect of the RIAT approach lies in it making use of a surrogate model which is able of capturing some of the non-linearity of a full-scale deterministic atmospheric model. Also, the multi-objective formulation of the problem is different from common approaches. However, there are several limitations of the approach: RIAT does neither address uncertainty nor non-technical measures. Furthermore, it applies an arbitrary weighting scheme in its objective function which contradicts social welfare maximization. This is not in line with the objectives laid out in chapter 1.5. The

shortcomings are discussed in more detail in the following section.

1. According to [Carnevale et al. \(2012b\)](#), the implementation of a two-objective approach by weighting multiple AQIs in the first objective function is intended to ease the visualization and the understanding of the results. Conceptually, this may be considered controversial. Note that the AQIs of RIAT deal with quite different impacts which cannot be trivially weighted against each other. For instance, the AQI dealing with SOMO35 is concerned about human health impacts whereas AOT40 deals with impacts on vegetation. Any weighting scheme of meeting predefined target levels of the aforementioned indicators makes a lot of implicit but non-obvious and non-trivial assumptions on preferences and impact valuation. Linear combinations of different impacts dealing with different endpoints can only justifiably be made when conducting integrated impact assessment like the IPA (cf. [Bickel and Friedrich \(2005\)](#)).
2. Multi-objective programming, as the name suggests, is intended to consider multiple objectives simultaneously. Leaving aside difficulties with determining a weighting scheme for the first objective dealing with air quality, it is not made transparent how the MOP solver tackles the problem of optimizing the two-objective problem of balancing air quality versus implementation cost of measures. Many problems arise from this formulation as it involves potential weighting schemes or scaling schemes with respect to the two objectives. The general limitations of multi-criteria decision analysis were already discussed. They also apply in this context (see chapter 1.3).
3. Other objectives which should be included in an IAM are not considered in RIAT, most prominently climate change impacts. RIAT looks at cost-effectiveness of strategies to meet AQI targets and aims to reduce uncertainty of air quality estimates by applying ANNs. However, when conducting a CBA to determine cost-efficient solutions, it is revealed that uncertainties of other steps of comprehensive IAM are larger and hence more important, mainly: For instance, geometric standard deviation (GSD) of monetization of impacts and assessment of climate change impacts are higher by about a factor of 2 or 3, respectively (cf. [Rabl et al. \(2014\)](#)).
4. Non-linearity is only considered with respect to source-receptor modelling in RIAT. This may seem sufficient when considering only end-of-pipe technology options as

opposed to also assessing behavioural change. In the RIAT problem formulation, this may in fact be the most prominent source of non-linearity. However, when also considering non-technical measures it is observed that the effect of non-linearity due to behavioural change largely surpasses the impact of non-linear effects of SR relationships.

5. [Carnevale et al. \(2012b\)](#) admits that uncertainties in RIAT are not properly accounted for as is the case in other IAM approaches. When applying RIAT to determine cost-effective strategies, the risk that policy-makers may face cannot be quantified with respect to meeting the target levels of AQIs. Also, the authors do not mention concepts similar to the precautionary and no-regret applied in GAINS. However, the disadvantages of these approaches were already discussed above.

1.4.4 ExternE and UWM

The Uniform World Model (UWM) does not intend to provide a full framework for CEA or CBA of potential policies. Even though specifically aimed at being used for benefit assessment and its economic valuation, the results from the UWM cannot be directly used for decision making but serve as input for such models. However, it is listed here for its innovativeness with respect to assessing uncertainties along the IPA. Recall that none of the aforementioned IAM approaches properly deals with uncertainty when determining environmental impacts.

The UWM was developed by [Curtiss and Rabl \(1996\)](#) and [Spadaro \(1999\)](#). It was extended and applied in the scope of the methodology update of the ExternE series ([Bickel and Friedrich, 2005](#)). The model deals with the impact and valuation of pollution and is intended to provide region-typical as opposed to site-specific results. It is presented in detail along with a thorough discussion of related uncertainties of the IPA steps in [Rabl et al. \(2014\)](#). The spreadsheet implementation of UWM, named RiskPoll, is publicly available.

For the sake of simplicity when estimating total damages from air pollution in a uniform world, the UWM assumes uniform receptor density, uniform atmosphere and uniform dose-response function slope ([Curtiss and Rabl, 1996](#)). To analyse environmental im-

pacts the model follows the impact pathway methodology from characterization of relevant technologies and the environmental burdens they impose, calculating the changed pollution concentration in affected regions, determination of physical impacts using dose-response functions (DRFs) and a final economic valuation of these impacts. The total damage is the sum over all affected receptors.

The authors state that the site-dependence is surprisingly small in the example of [Curtiss and Rabl \(1996\)](#), however more recent studies praise the advantages of more detailed analyses. The authors claim that their results are correct in one order of magnitude. However, this may not be sufficient in the context at hand. More recent studies also found that there is considerable influence of specific parameters, for instance when dealing with impacts in urban compared to rural regions ([Torras Ortiz and Friedrich, 2013](#)).

1.5 Contributions of this thesis

Limitations of existing work are thoroughly discussed in chapter 1.4. This part deals with the contributions of this work to achieve the objectives listed in chapter 1.2. For the sake of comprehensibility, the two objectives are repeated here and the individual contributions of this work are specifically outlined. Recall that the first objective is as follows:

O1: Enable decision-makers to determine cost-efficient outcomes under different levels of risk aversion.

The contributions to this objective are threefold:

- An innovative stochastic optimization approach that consistently incorporates uncertainty of environmental impacts and uncertainty of people's responses to policy implementation is developed and presented. It conducts optimal policy selection and parametrization of policies to determine cost-efficient environmental protection strategies by trading-off the avoidance of uncertain environmental impacts against uncertain costs and loss of surplus.
- Impacts are accounted for by utilizing economic valuation schemes, e.g. along the

IPA chain in the context of air pollution. Therefore, uncertainty analysis along the full IPA chain was carried out to estimate probability distributions of all relevant model parameters concerned with estimating impacts.

- The approach developed in this thesis accounts for specific risk attitudes of a decision-maker in the formulation of the objective function of the stochastic optimization problem via a single parameter (ϕ). The level of risk aversion is represented via risk measures in the objective function. Risk aversion and risk neutrality can be weighed against each other and their relative impact is assessed by sensitivity analysis of the weighting factor.

The approach described in this thesis aims to model multiple non-linear responses to policy which is important if substitutes are available (e.g. in public transport). Also, it supports conjoint application of multiple policies. Thus, the reader is reminded that the second objective of this thesis is as follows:

O2: Enable decision-makers to conduct a conjoint assessment of policies inducing behavioural change along with considering technical options.

Contribution to this objective laid out in this thesis are as follows:

- A methodology was developed which properly deals with outcomes of conjoint application of multiple policies. This is achieved by substitution processes between modes of transport. In the context of behavioural change the response is quantified by elasticities. Proper substitution is ensured via a set of identity equations. The elasticities describe and quantify the relative non-linear behavioural change (e.g. change in individual transport demand) in response to the implementation of a specific policy affecting a certain characteristic of an activity (e.g. price components like tolls or taxes on fuel). The response in the model results in a dynamic shift of mode-specific transport demand until the cost-efficient solution is determined. The concept of elasticities also allows to partially estimate demand curves which in turn supports the proper estimation of utility changes. Additionally, avoided or induced externalities are included in the benefit-cost analysis.
- The high levels of uncertainty and non-linearity of the behavioural change are dealt with as follows: First, a deterministic continuous non-linear methodology is devel-

oped and modelled in an optimization framework. Secondly, a piece-wise linear approximation (PLA) approach is developed to derive a linear model. Reformulating the non-linear terms makes the approach more tractable for solvers. This turns the problem into a Mixed Integer Problem (MIP). Thirdly, a stochastic version is derived and the objective function is adjusted as described under objective O1.

- To properly estimate the effects of non-technical measures in the passenger transport sector, an extensive MRA is conducted. However, very few studies so far are concerned with properly transferring elasticity estimates from past studies to a different context. Instead, rule-of-thumb values or best guesses are often applied. In this work, meta-regression models are developed specific to certain policy instruments (e.g. fuel tax adjustment or city tolls). The models are fed with collected meta-information of the literature found or information mentioned therein like study year, country or city of the study. Subsequently, the dataset is enriched with general statistics like gross domestic product (GDP), population density, rail network length and similar. The meta-regression models are then able to transfer empirical findings to other contexts. The models are developed specific to certain policy instruments (e.g. fuel tax adjustment or city tolls).

Results of a case study are presented in this thesis to showcase the major features of the modelling framework. The study investigates how improvements can be achieved in the passenger transport sector of the EU28+2. Outcomes of a sensitivity analysis are discussed afterwards.

A further contribution of this work is that the model also estimates the response of different socio-economic groups to a policy instrument. This is a side-effect of two aspects that were represented in the modelling framework: Firstly, low-income groups respond differently to policy instruments like fiscal incentives which can be related to their lower disposable income. Thus, elasticity values are modelled per income group to capture the different response of the less-wealthy to changes in price. For this purpose, country- and mode-specific Lorenz curves are developed using a multi-model inference approach relying on limited public statistics. Secondly, vehicle types and technologies are associated with income groups as well to represent the fact that older vehicles tend to be more polluting while at the same time these vehicles are traditionally operated by the less-wealthy. In

summary, there is a tendency of lower-income people driving less but responding stronger on the one hand, but operating more polluting vehicles on the other hand.

2 Methodology

In the following chapter 2.1 the general system boundaries of the approach developed in this thesis are described. The deterministic model formulation is developed in chapter 2.2. In the deterministic case one can only deal with policy-makers having a risk-neutral stance. An extension to the stochastic case follows afterwards in chapter 2.3 and a representation of risk attitudes is shown in chapter 2.5. The stochastic model enables the representation of more complex preferences and risk attitudes of the decision-maker. To cope with non-linear terms during optimization an approximation methodology utilizing piece-wise linear approximation (PLA) is developed and presented in chapter 2.4. An important advantage over existing models is that the proposed methodology is not specific to a given sector but can be generally applied to different policy questions.

To relate what follows to the case study presented in chapters 3 to 6 the focus is on examples that illustrate the application within the passenger transport sector. Furthermore, by utilizing the proposed approach decision-makers are enabled to estimate the effects of non-technical measures as a behavioural response to policies, which is another innovation in this context. Additionally, the representation of risk aversion is taken care of by a stochastic model.

2.1 System boundaries

When investigating avoided damages due to the implementation of policies it is imperative to consider changes in both direct and life-cycle emissions to represent the effects. Consider as an example the case of a transport policy which induces a modal shift, say from individual transport to public transport: While one activity level decreases, the initial demand of transport will not vanish but instead will be served by an alternative, less polluting mode. To properly determine the change in pollution levels one needs to consider exhaust and non-exhaust emissions of the respective vehicles on the one hand, but needs to account for life-cycle emissions of the respective modes as well. This includes processes like fuel extraction and refining as well as the distribution of fuel. Thus, this

work considers not only the direct effect of policy interventions but also accounts for the impacts of up-stream emissions arising due to changes in supply.

Essentially, a partial equilibrium is determined to find an optimal policy selection. This implies that major policy-induced economic effects outside of the sector of interest are considered to be of marginal size. Going back to the example of policies in the transport sector, one may consider a modal shift from individual transport to public transportation systems. This will obviously lead to a reduced demand of fuel. In this example, the up-stream emissions due to less production of fuel including its production in refineries and its distribution and supply is included in the analyses. This is also the case for induced additional up-stream emissions due to the increased demand of electricity or fuel to power alternative passenger transport systems by metro or tram, for instance. However, effects that any reduced demand of fuel may cause outside of the transport sector are not accounted for, including potential structural adjustments of the economy.

2.2 Deterministic model formulation

In the following chapter the model formulation is developed within a consistent mathematical framework. The focus is on the deterministic case. This will later be extended to the stochastic case in chapter 2.3.

First, the ambition of social welfare maximization is formalized in chapter 2.2.1. It aims to balance benefits and cost and formalizes the goal towards which policies should be implemented. To account for proper implementation of policies, several identity equations are defined in chapter 2.2.2. These equations ensure that all initial demand is still supplied after policy intervention. However, the activity levels may have potentially moved to a different category or technology. It is warranted that the representation of behavioural change is supported by quantitative evidence on cross-elasticities. Thereby, induced utility gains or losses are also properly accounted for. Finally, the estimation of impacts on human health and the environment due to policy intervention is formalized in chapter 2.2.3.

2.2.1 Objective function

The objective of the model is to determine a combination of policies which results in maximum overall benefit for society, i.e. the maximum net present value of the total benefit as sketched above. Maximizing net benefit is equivalent to minimizing the overall social cost represented by subtracting from the avoided damages the loss of utility or surplus and subtract the economic costs including additional state subsidies. The surplus is the consumer's monetary gain which is obtained by being able to consume a product below a price level he or she would actually be willing to spend. Therefore, the model determines the optimal policy parameter selection as a function of avoided damages $D_{I,C}$, loss of surplus $L_{I,C}$, and economic costs $S_{I,C}$. These values are determined for each country C and each socio-economic group I . The indices I and C require careful interpretation as to whether they affect a specific group of people or whether they are caused by that group: In the case of avoided damages $D_{I,C}$, this covers damages *caused* by activities conducted by members of I in country C . Due to the trans-boundary nature of pollution these may very well affect individuals in other countries $C' \neq C$, and may also affect members of a different socio-economic group $I' \neq I$. Secondly, the loss of surplus $L_{I,C}$, covers the reduction in additional utility that directly *affects* members of group I in country C when switching from one type of activity to another. The costs $S_{I,C}$ have to be spent by society as a whole to *support* the policy intervention that affects members of group I in country C .

The overall goal is to find a reallocation that better serves society as a whole. It is important to recognize that this does not imply that the costs are accounted for by the people that are causing them nor by the ones that are affected. Instead, the reallocation is judged based on whether it leads to a Pareto improvement and whether those made better off could compensate those being made worse off. In welfare economics this is known as the Kaldor-Hicks criterion.

The degree of implementation of technical options and the degree of adaptation through behavioural response to policies are represented by the variables of the optimization problem, namely \mathbf{x} and ζ , respectively: The vector ζ consists of the independent variables representing the degrees of implementation of technical options. The independent variables representing degrees of adaptation through behavioural response are elements of

vector \mathbf{x} . The effects of \mathbf{x} and ζ on the objective function will be addressed within the remainder of this chapter. Note that the independent variables in \mathbf{x} will be replaced by λ due to the application of PLA in chapter 2.4.

The deterministic objective function for the risk-neutral case can be written as follows:

$$\max Z(\mathbf{x}, \zeta) = \sum_{I,C} \left(D_{I,C}(\mathbf{x}, \zeta) - L_{I,C}(\mathbf{x}) - S_{I,C}(\mathbf{x}, \zeta) \right) \quad (2-1)$$

where

Z is the objective function representing the net benefit for society,

$D_{I,C}$ is the amount of avoided damages caused by activities conducted by members of I in country C ,

$L_{I,C}$ is the reduction in additional utility that affects members of group I in country C , and

$S_{I,C}$ is the total economic cost to be spent by society to support policy intervention affecting members of group I in country C .

In the following paragraphs the determination of the individual variables $D_{I,C}$, $L_{I,C}$ and $S_{I,C}$ are discussed, starting with the avoided damages $D_{I,C}$. For the sake of improved readability the indices I and C are dropped in the subsequent notation. The reader is expected to implicitly acknowledge the differentiation by income group and country where required.

First, the determination of $D_{I,C}$ is addressed. Technology-specific damages are commonly assumed to be linear in the amount of activity. This is known to be a valid assumption in the European context (cf. WHO (2013a)). However, the model developed in this thesis may also be applied in a context where damages are known to be non-linear in the level of activity. This is the case in regions with very high baseline pollution levels as is the case in China, for instance. These effects can be easily accounted for by applying a PLA on the dose-response functions (DRFs). The same methodology is applied in the context of estimating the effects of non-linear demand changes due to policy application. The reader is referred to chapter 2.4 for details.

In the interest of enhanced comprehensibility some indices will again be omitted, namely the region (R) and period (PD) indices of the variables. Though region and period are important to be considered in the problem context they do not add extra complexity to the problem. It is assumed that baseline demand levels are given. They are denoted by $\hat{a}_{K,T}$ where K is a category and T is a technology. In the case of passenger transport, K is a vehicle category and T is a technology which can be linked to specific per-unit levels of pollution. In the linear case, the avoided damages summed over all pollutants P can be determined as follows:

$$D(\mathbf{x}, \zeta) = \sum_{P,K,T} \left(\hat{a}_{K,T} - a_{K,T}(\mathbf{x}, \zeta) \right) \Phi_{K,T,P} \quad (2-2)$$

where

$\hat{a}_{K,T}$ is the fixed initial reference level of activity conducted within category K by technology T ,

$a_{K,T}$ is the variable level of activity conducted within category K by technology T , and

$\Phi_{K,T,P}$ is the monetized impact caused by the release of pollutant P per unit of activity of category K and technology T .

Note that the monetized impact parameter $\Phi_{K,T,P}$ depends, obviously, also on the location of the source of the emission, thus on country and region (e.g. urban or non-urban). The determination of $\Phi_{K,T,P}$ is described in more detail in chapter 2.2.3 As aforementioned, the indices were dropped for the sake of readability only. The final level of activity, denoted by $a_{K,T}$, is determined by considering the effects of policy intervention. It is described in detail in chapter 2.2.2.

Apart from the positive effects of avoiding damages there are also adverse effects. One of them is a potential loss of utility as a result of a previously existing surplus. In the following the total loss of utility $L_{I,C}$ of socio-economic group I in country C and the necessary public spendings to support the effects experienced by the respective group, i.e. $S_{I,C}$, are defined. In the scope of transport policies the latter term covers increased state subsidies to provide facilities to people that perform a modal shift from individual motorized traffic to public transport.

Recall that the degree of implementation of technical options and the degree of adaptation through behavioural response to policies are represented by \mathbf{x} and ζ , respectively. The policies eliciting behavioural response address a characteristic Q of a certain activity category K . The degrees of adaptation are represented by elements of vector \mathbf{x} .

The total loss of surplus is set to

$$L(\mathbf{x}) = \sum_{K,T} \sum_{Q,K',T'} u_{K,T,Q,K',T'}(\mathbf{x}) \quad (2-3)$$

where

$u_{K,T,Q,K',T'}$ is the utility lost when serving a given demand by category K' and technology T' which was previously served by category K and technology T due to change in Q ,

and the economic cost is given as

$$S(\mathbf{x}, \zeta) = \sum_{K,T} \left(\sum_{Q,K',T'} s_{K,T,Q,K',T'}(\mathbf{x}) + \sum_{M,T''} \left(A_{K,M} \zeta_{K,T,M,T''} \right) \right) \quad (2-4)$$

where

$s_{K,T,Q,K',T'}$ is the additional non-private spendings needed to cover responses to Q , i.e. to be able to serve demand by category K' and technology T' which was previously served by category K and technology T ,

$A_{K,M}$ is the annuity cost of technological option M per unit of K , and

$\zeta_{K,T,M,T''}$ is the shift from a demand previously served by category K and technology T to T'' of the same category due to technological option M becoming available.

The change in surplus and change in non-private spendings are a result of a behaviour-induced activity shift from (K, T) to (K', T') due to changes in Q . The total, i.e. investment and operational, cost of technical option M are covered by an annuity A_M . This will be defined in eq. (2-7). The effects of policy intervention in terms of both activity changes and annuity cost are discussed in the remainder of this chapter.

In what follows identity equations will be developed to ensure balance in serving all

demands after policy intervention though with likely different activities. It is also ensured that costs including the cost of technological shift as well as utility losses due to behavioural changes are properly incorporated.

2.2.2 Identity equations

The aforementioned definitions of benefits and costs (eq. (2-1) to eq. (2-4)) rely on the substitution of activity. Behavioural change is represented by \mathbf{x} and induces modal shifts from one category K to another category $K' \neq K$. Technical options allow transition within the same category K but from one technology T to another $T' \neq T$. This is represented in the model by ζ .

To ensure overall balance several identity equations are introduced and discussed in this section. Each identity equation holds true independent of the value of the individual variables. This assures that all initial demand is supplied after policy intervention though potentially by different category-technology combinations.

Therefore, the most relevant identity equation describing the effects of policy implementation is the one that holds balance during the substitution process. Therefore, one may set

$$a_{K,T}(\mathbf{x}, \zeta) = \hat{a}_{K,T} + T_{K,T}(\zeta) + B_{K,T}(\mathbf{x}) \quad (2-5)$$

where

$a_{K,T}$ is the variable level of activity conducted by category K and technology T ,

$\hat{a}_{K,T}$ is the fixed initial reference level of activity conducted by category K and technology T ,

$T_{K,T}$ represents total shift to (K, T) due to technological measures, and

$B_{K,T}$ represents total shift to (K, T) due to behavioural adaptations.

Note that both $T_{K,T}$ and $B_{K,T}$ may be negative. In the following the two different adaptation techniques are described that may be caused by policy intervention. First, technological shifts represented by $T_{K,T}$ in eq. (2-5) are addressed (cf. eq. (2-6)). Such shift may be caused by policy regulations that forbid the use of certain technologies

in specific regions or constrain the use of technologies by reduction goals. Potential technological options in the scope of the transport sector are discussed in chapter 5. Secondly, behavioural change as a response to policy implementation represented by $B_{K,T}$ in eq. (2-5) is discussed (cf. eq. (2-8)). A sound mathematical representation is discussed in the following paragraphs. Data collection via literature research for a number of policies that aim to induce behavioural change in the scope of the transport sector is presented in chapter 4.

Policy-induced technological shift can be represented as follows:

$$T_{K,T}(\zeta) = \left(\sum_{M,T'} \zeta_{K,T',M,T} - \zeta_{K,T,M,T'} \right) \quad (2-6)$$

where

$\zeta_{K,T',M,T}$ is the shift from a demand previously served by category K and technology T' to T of the same category due to option M becoming available, and

$\zeta_{K,T,M,T'}$ is the shift from a demand previously served by category K and technology T to T' of the same category due to option M becoming available.

T' may be an existing technology which already exists in the reference case. Then, M can be interpreted as a retrofit option to be applied on T . T' can also represent an entirely new technology which is not present in the reference scenario. In both cases M has very likely investment and potential operational cost associated to it which have to be considered when estimating overall net benefit.

Investment costs represent an initial payment of the end-user or the society at the beginning of the implementation of M . Annual cost that may occur, for instance, due to operation and maintenance of the technological option are summarized under operational cost. For a proper assessment of a technical measure in the scope of cost-benefit analysis (CBA) costs are usually combined and discounted over the estimated period of application. Following the approach of [EEA \(1999\)](#), this allows the determination of annuities for a given year as follows:

$$A_{K,M} = \kappa_{M,I} \left[\frac{r(1+r)^{n_M}}{(1+r)^{n_M} - 1} \right] + \kappa_{M,O} \quad (2-7)$$

where

$A_{K,M}$ is the annuity of option M for a given period, typically over the course of one year,

n_M is the estimated period of application of measure M in years,

r is the discount rate for a given period,

$\kappa_{M,I}$ is the investment cost of measure M at the beginning of implementation, and

$\kappa_{M,O}$ is the operational cost of measure M per year.

It is assumed that utility losses and gains are only associated with behavioural change and that a technical option does not cause any change in consumer surplus. It is further assumed that both $\kappa_{M,I}$ and $\kappa_{M,O}$ are given or can be transferred into per-unit of demand values. In the context of transport, this implies that investment cost and operational cost are given per person-kilometre (PKM). This allows proper comparison between different technologies of the same category on the one hand but also allows to estimate cost changes when a technology is also used more due to the shift between categories K and K' via behavioural change.

Having dealt with the adaptation of technical options the behavioural response to policies will be addressed in the following. The aspect of behavioural change as a response to policy implementation has widely been ignored in integrated assessment modelling (IAM) where the focus has been set mostly on technological adaptations similar to the approach presented above. This is partly due to complexity of properly representing behavioural response in a sound methodological framework and partly due to the lack of elasticity data or the considerable uncertainty of such data which is necessary to quantify responses. However, the importance of incorporating behavioural change and non-technical measures in IAM in general and air pollution modelling in particular is well-known in the scientific community (cf. e.g. [Sternhufvud et al. \(2006\)](#)).

The term $B_{K,T}$ is part of the activity balance eq. (2-5). The induced activity change due to policy implementation can be represented as follows:

$$B_{K,T}(\mathbf{x}) = \left(\sum_{Q,K',T'} \pi_{K',T',Q,K,T}(\mathbf{x}) - \pi_{K,T,Q,K',T'}(\mathbf{x}) \right) \quad (2-8)$$

where

$\pi_{K',T',Q,K,T}$ is the shift from a demand served by (K',T') to (K,T) induced by a change in characteristic Q , and

$\pi_{K,T,Q,K',T'}$ is the shift from a demand served by (K,T) to (K',T') induced by a change in characteristic Q .

In the above equation, substitutions of activity are subtracted from the initial reference levels. The modal shift from a demand served by (K,T) to (K',T') if it was induced by a change in Q is denoted by $\pi_{K,T,Q,K',T'}$. Q is a characteristic of (K,T) which was changed by a certain policy instrument, most often a price component. As a measure or response to the policy the demand is afterwards served by (K',T') .

To determine the actual effect, i.e. the amount of $\pi_{K,T,Q,K',T'}$ for a certain policy, one needs to know the cross-elasticity of (K',T') with respect to changes in component Q of (K,T) . Let us assume that the respective cross-elasticity $\eta_{K,Q,K'}$ is known. It describes the change of activity K and K' when the characteristic Q of K was changed.

The initial reference level of price component Q of category K is given and denoted by $\hat{x}_{K,Q}$. The optimal level, denoted by $x_{K,Q}$, is one of the independent variables in \mathbf{x} . The relative price level, $x_{K,Q}/\hat{x}_{K,Q}$, is easily determined and one can set

$$\pi_{K,T,Q,K',T'}(\mathbf{x}) = \begin{cases} t_{K,T} \hat{a}_{K',T'} \left[\left(\frac{x_{K,Q}}{\hat{x}_{K,Q}} \right)^{\eta_{K,Q,K'}} - 1 \right], & \text{if } \eta_{K,Q,K'} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (2-9)$$

where

$\pi_{K,T,Q,K',T'}$ is the modal shift from a demand served by (K,T) to (K',T') induced by a change in characteristic Q ,

$t_{K,T}$ is share of technology T within category K ,

$\hat{a}_{K,T}$ is the fixed initial reference level of activity conducted by category K and technology T ,

$x_{K,Q}$ is a vector element of \mathbf{x} and the variable level of price component Q of category K ,

$\hat{x}_{K,Q}$ is the fixed initial reference level of price component Q of category K , and

$\eta_{K,Q,K'}$ is the cross-elasticity of demand of K' with respect to component Q of K .

Going again back to the example of transport policy intervention, K may, for instance, refer to individual motorized transport by car, and K' may represent bus travel. Then, Q in eq. (2-9) could refer to fuel cost per PKM driven by car. Note that $x_{K,Q}$ is a vector element of \mathbf{x} . Being one of the variables under optimization it is part of a non-linear term which renders the whole optimization problem non-linear. This issue is dealt with by employing a PLA which turns the problem in a linear Mixed Integer Problem (MIP). The approach is later described in chapter 2.4. A positive cross-elasticity describes the behaviour that an increase in price component Q of K will result in some amount of activity being shifted from (K, T) to (K', T') . This is assured by eq. (2-5) which ensures balance after substitution of activities.

Having defined all terms of the identity equations accounting for demand balance allows for a determination of the avoided damages by inserting eq. (2-5) into eq. (2-2) to estimate the activity change. Additionally, it is important to consider the loss of surplus that arises due to modal shifts by determining how much surplus is lost by applying a policy scenario \mathbf{x} . Therefore, the additional utility lost by shifting amount $\pi_{K,T,Q,K',T'}(\mathbf{x})$ of activity from (K, T) to (K', T') is determined.

Being able to determine behavioural change, it is important to properly account for losses of surplus. The total loss $L_{I,C}$ is given in eq. (2-3) and the terms are determined as follows. Generally, the surplus can be interpreted as the area under the demand curve and above the horizontal line marking the actual price. The exact demand curve is not known but one can construct induced demand changes due to policy application from the respective cross-elasticity values. If the demand curve was linear one could state that for $\eta_{K,Q,K'} > 0$ the loss of additional surplus – i.e. surplus above the money actually spent – is estimated using the well-known approximation of the rule of a half (RoH). The concept of RoH is explained later in more detail. However, for the situation at hand one can even determine a better approximation of the loss of additional surplus as follows. Consider the isolated change, say raise, of $\hat{x}_{K,Q}$ to $x_{K,Q}$ where for all other $K'' \neq K$ the following holds: $x_{K'',Q} = \hat{x}_{K'',Q}$; for all $Q'' \neq Q$ one sets $x_{K,Q''} = \hat{x}_{K,Q''}$ and $x_{K'',Q''} = \hat{x}_{K'',Q''}$. This ensures an isolated price change while all other prices remain at the reference level,

also prices of other components of the same activity category. This scenario is denoted by \mathbf{x}^* . For simplicity assume that there is only a single K' such that $\eta_{K,Q,K'} \neq 0$. As a result there is a modal shift from K to a single other category K' . Without loss of generality one may further assume $\eta_{K,Q,K'} > 0$ so that $\pi_{K,T,Q,K',T'}(\mathbf{x}^*) > 0$. Then, one can use eq. (2-5) and is able to easily estimate the partial demand curve of activities of type (K, T) as follows:

$$a_{K,T}(\mathbf{x}^*) = \hat{a}_{K,T} - \pi_{K,T,Q,K',T'}(\mathbf{x}^*) \quad (2-10)$$

where

$a_{K,T}$ is the variable demand of activity conducted by category K and technology T ,

$\hat{a}_{K,T}$ is the fixed initial reference level of activity conducted by category K and technology T ,

$\pi_{K,T,Q,K',T'}$ is the modal shift from a demand served by (K, T) to (K', T') induced by a change in characteristic Q .

Therefore, one can estimate the loss of surplus by integrating over the demand from $\hat{x}_{K,Q}$ to $x_{K,Q}$. This is correct and exact for an isolated change of $x_{K,Q}$, i.e. the definition of \mathbf{x}^* . However, from eq. (2-5) one may see that this is an approximation for $x_{K,Q}$ when other $x_{K'',Q''}$ ($K'' \neq K$, $Q'' \neq Q$) change simultaneously. For the case of changes in other price components of the same category ($K'' = K$, $Q'' \neq Q$), for instance raised toll prices along with simultaneously raised fuel prices, this seems a valid assumption as the elasticities $\eta_{K,Q,K'}$ and $\eta_{K,Q',K'}$ have been observed or modelled separately and, thus, refer to a different reference scenario anyway. Therefore, one can assume that the introduced modelling uncertainty is covered by the ranges of elasticities in the stochastic model which cover other effects inherently. An important benefit of using the following equation to approximate the utility loss is that the overall estimated impact of the policy scenario is indifferent to the order of policy application.

For cases in which $x_{K,Q} > 0$, one does not need to approximate using the RoH and assume linearity. Instead, one can estimate the loss of using the above equation eq. (2-10) in point

\mathbf{x}^* given $\eta_{K,Q,K'} > 0$ as follows

$$\begin{aligned}
\Pi_{K,T,Q,K',T'}(\mathbf{x}^*) &= \int_{\hat{x}_{K,Q}}^{x_{K,Q}} \pi_{K,T,Q,K',T'}(\mathbf{x}^*) dx_{K,Q}^* & (2-11) \\
&= \int_{\hat{x}_{K,Q}}^{x_{K,Q}} t_{K,T} \hat{a}_{K',T'} \left[\left(\frac{x_{K,Q}}{\hat{x}_{K,Q}} \right)^{\eta_{K,Q,K'}} - 1 \right] dx_{K,Q}^* \\
&= \left[t_{K,T} \hat{a}_{K',T'} x_{K,Q}^* \left(\frac{\left(\frac{x_{K,Q}^*}{\hat{x}_{K,Q}} \right)^{\eta_{K,Q,K'}}}{\eta_{K,Q,K'} + 1} - 1 \right) \right]_{\hat{x}_{K,Q}}^{x_{K,Q}} \\
&= u_{K,T,Q,K',T'}(\mathbf{x}^*) \\
&\approx u_{K,T,Q,K',T'}(\mathbf{x})
\end{aligned}$$

where

$\Pi_{K,T,Q,K',T'}$ is the indefinite integral of $\pi_{K,T,Q,K',T'}$,

$u_{K,T,Q,K',T'}$ is the utility lost when serving a demand by category K' and technology T' which was previously served by category K and technology T ,

$\pi_{K,T,Q,K',T'}$ is the modal shift from a demand served by (K, T) to (K', T') induced by a change in characteristic Q ,

$t_{K,T}$ is share of technology T within category K ,

$\hat{a}_{K',T'}$ is the fixed initial reference level of activity conducted by category K' and technology T' ,

$x_{K,Q}$ is the variable level of price component Q of category K ,

$\hat{x}_{K,Q}$ is the fixed initial reference level of price component Q of category K , and

$\eta_{K,Q,K'}$ is the cross elasticity of demand of K' with respect to price component Q of K .

For $\eta_{K,Q,K'} \leq 0$ one can set $\Pi_{K,T,Q,K',T'}(\mathbf{x}^*) = 0$ representing no loss of utility. In the above equations Q denotes the set of individual characteristics of a certain activity. In the case study this represents cost components of a certain transport mode. It represents the cost that individuals face when taking a decision on a certain mode of transport. So it may, for instance, contain fuel cost as an element for operating a car for a certain

trip as opposed to using a public transport option. For the latter an element in Q may refer to ticket fare for instance. In the context of the study conducted in this thesis, one can consider an element in Q a cost component of transport, but in theory it may represent any kind of characteristic of an activity, i.e. cost in a broader more abstract sense. Sticking with our example of different transport modes it may also represent travel time, quality of service or waiting time both in-vehicle or outside of a vehicle. This leaves a lot of flexibility in dealing with cross-elasticities as they are not only measured in terms of a certain price component.

It is important to note that the proposed methodology of determining the demand change due to price changes via cross-elasticities, and elasticities in general, can only be applied when there was already an existing non-zero price component $x_{K,Q} > 0$. The concept of log arc elasticities cannot be applied in certain settings: For the case when $x_{K,Q} = 0$ for a certain price component Q – take as an example the case of introducing distance-based tolls in places that did not have any tolls at all. In fact, the resulting demand is not computable when any of the affected demands is zero initially which is the case when $\hat{a}_{K,T} = 0$ or $\hat{a}_{K',T'} = 0$. Given such conditions other approaches need to be applied. Except for very large changes in demand or price a reasonable approximation can be achieved when applying the mid-point arc elasticity. The concept of mid-point elasticities may be utilized to determine demand changes instead. It is impossible to determine a respective partial demand function for this case. But one can estimate the change in demand and the RoH is used to estimate the loss of surplus. The concept is a widespread approximation of the change of consumer surplus in transport appraisal. It has been used since the end of the 1960s and is the recommended approximation method for transport-related consumer surplus estimation (cf. Williams (1977) in Winkler (2015)). The methodology is also recommended for in-practice estimation of user benefits by the United Nations Economic Commission for Europe (UNECE) (UNECE, 2008). The rule assumes that the demand curve is linear between the demand levels given at prices $\hat{x}_{K,Q}$ and $x_{K,Q}$, respectively.

Having defined the substitution processes, it is only term $s_{K,T,Q,K',T'}$ in $S_{I,C}$ left to be addressed. For the sake of simplicity and without loss of generality, the following work deals with direct cost components of transport as they need to be looked at separately

as well. Urban public transport is to a large extent subsidized by the state to lower the individual costs of utilizing public transport systems, i.e. the ticket price (cf. Kugler (2012)). As one needs to consider these public costs in terms of investment costs and state subsidies that are induced by people's response to a policy, the set of cost components Q needs to be extended. Still Q refers to those characteristics or cost components an individual faces. Additionally, public cost components are denoted by $Q^{(p)}$. Consider state subsidies as a representative of public costs. One can calculate the induced public costs of modal shift from (K, T) to (K', T') as follows:

$$s_{K,T,Q,K',T'}(\mathbf{x}^*) = \sum_{q \in Q^{(p)}} \pi_{K,T,Q,K',T'}(\mathbf{x}^*) \left(\hat{x}_{K',q} - \hat{x}_{K,q} \right) \quad (2-12)$$

where

$Q^{(p)}$ is a set of cost components the public faces,

$s_{K,T,Q,K',T'}$ is the additional non-private spendings needed to cover responses to Q , i.e. to be able to serve demand by category K' and technology T' which was previously served by category K and technology T ,

$\pi_{K,T,Q,K',T'}$ is the shift from a demand served by (K, T) to (K', T') induced by a change in characteristic Q , and

$\hat{x}_{K,q}$ is the fixed initial reference level of direct non-private cost price component q of category K .

This is used in eq. (2-4) to estimate overall change in non-private spendings including funding via state subsidies.

2.2.3 Externalities

This chapter deals with the formulation of externalities in the form of health effects and climate impacts. The general objective of the framework is to trade off the costs in terms of individual utility loss and monetary costs with the benefits of avoided externalities (cf. chapter 2.2.1). This section presents how the benefits of avoiding harmful effects that occurred before policy intervention are represented in the model. One may potentially

include many environmental impacts across multiple media like air, soil and water. However, in this section the methodological framework is laid out with respect to the most harmful impacts, namely air pollution and climate change. Obviously, the methodology can be extended to include more stressors, media or pathways. It has to be noted that this introduces epistemic uncertainty as particular data are hidden from the optimization approach. In the context of this thesis the effects are considered minor as other impacts are much smaller (cf. [Genius \(2016\)](#)).

Adverse health impacts due to air pollution are considered with emphasis on mortality effects via intake (i.e. inhalation) of fine particles (particles of aerodynamic diameter of less than 2.5 micron, $PM_{2.5}$) and nitrogen dioxide (NO_2). These pollutants have been shown to increase the relative risk to suffer from various disease leading to a considerable reduction of lifetime for individuals (e.g. [Hoek et al. \(2013\)](#)).

Global warming impacts are accounted for in this thesis, though associated uncertainties are difficult to estimate due to the extensive temporal decoupling of cause and impact. Due to the impact occurring much later in time than the release of emission there are large uncertainties and possible gaps in the impact pathway approach to estimate damage costs of climate change. Therefore, it is instead recommended to assess the cost of avoiding the emission release in the first place under a given predefined environmental target. This is done by applying the standard price approach. The approach requires a given environmental protection target which should be agreed on by involving the affected actors and is accepted by society as a whole. A common example is the domestic reduction target for CO_2 -equivalent (CO_2eq) by 80% below 1990 levels as aimed for by the EU until 2050. The standard price approach determines the cost of reaching this target and interprets the necessary costs as society's willingness-to-pay (WTP). Therefore, the costs do not depend on the avoided damage that may have occurred, but instead depend on the agreed environmental targets.

In this work, impact on ecosystems are not included. Economic valuation of ecosystem components and functions has long been put in second place in the literature but has become more prominent recently ([de Groot et al., 2012](#)). Damages to ecosystems occur for instance due to unnatural over-enrichment of bodies of water with plant nutrients (eutrophication) leading to a loss of biodiversity in the ecosystem. Impacts induced by

the loss of biodiversity are particularly difficult to assess. Commonly, one assess damage cost or loss of value when assessing environmental cost to trade off the cost against the impact of policies. Therefore, the possibility of substitution is assumed in neoclassical environmental economics. Obviously, this becomes difficult when there is no comparable entity that can be interpreted as option for substitution to quantify the loss of value and, hence, monetize the damage. Also, substitution is not possible if the ecosystem is affected by irreversible damage or if essential ecosystem services are destroyed. It is stressed that the framework developed in this thesis is, in theory, capable of incorporating such monetized impacts of damages to ecosystems.

In what follows the Impact Pathway Approach (IPA) is formulated to fit the framework developed in this thesis in order to calculate damage costs that arise from the emission of a certain amount of a pollutant at a specific place. To determine the impact of conducting an activity (K, T) one needs to determine the amount of emission released. For environmental impacts the source location of emission release is an important factor. The impact of the emission release will occur both locally at the source site but due to transport and potential chemical transformation of the emitted pollutants other more distant receptors may as well be affected. Therefore, the whole impact chain needs to be considered to properly account for damages and risks. The impacts will be monetized to represent the loss due to the adverse effects on health (see above).

The impact pathway chain allows to estimate marginal damage cost, i.e. monetized damages that occur (or are avoided) due to an additional (or reduced) unit of activity. The environmental cost of one unit of several modes of transport are of particular interest in the case study.

For a pollutant P one may determine the amount of annual emissions as follows:

$$e_{K,T,P}(\mathbf{x}, \zeta) := a_{K,T}(\mathbf{x}, \zeta) f_{K,T,P} \quad (2-13)$$

where

$e_{K,T,P}$ is the total emission of P released due to activity of (K, T) under the given scenario,

$a_{K,T}$ is the variable level of activity conducted within category K by technology T ,
and

$f_{K,T,P}$ is the emission factor of (K, T) with respect to pollutant P , i.e. the amount released per unit of activity of K .

Note, that the emission factor (EF) denoted by $f_{K,T,P}$ may be a highly uncertain factor in the overall impact pathway chain, i.e. that the unit emission for a certain activity may be uncertain by an order of magnitude or may be well-known. This is accounted for in the stochastic formulation (see chapter 2.3) by introducing random variables $f_{K,T,P}(\omega)$ for a given scenario realisation ω .

Another important source of uncertainty is the estimation of damage caused by the release of a certain amount of pollution. For a number of impacts γ one aims to determine the impact caused by conducting aforementioned activity, i.e. one strives to calculate the impact $I_{K,T,P}^{(\gamma,P')}(\mathbf{x})$ which can be formulated as follows:

$$I_{K,T,P}^{(\gamma,P')}(\mathbf{x}, \zeta) = \int_{\mathbf{r}} c_{P'}(\mathbf{r}, e_{K,T,P}(\mathbf{x}, \zeta)) \delta(\mathbf{r}) m^{(\gamma,P')}(\mathbf{r}) d\mathbf{r} \quad (2-14)$$

where

$I_{K,T,P}^{(\gamma,P')}$ is the annual rate of impact γ due to exposure to P' ,

$e_{K,T,P}$ is the total emission of precursor P released due to activity of (K, T) under the given scenario,

\mathbf{r} is the location of a receptor,

$\delta(\mathbf{r})$ is the density of the receptor at location \mathbf{r} ,

$c_{P'}$ is the change in concentration of pollutant P' , and

$m^{(\gamma,P')}$ is the slope of the respective concentration-response function (CRF).

Here, γ can be one of the aforementioned impacts, for instance premature mortality due to exposure to air pollution, measured in cases per year. The specific pollutant P' may be different from the released precursor emission P , e.g. the emission of NH_3 may eventually form $\text{PM}_{2.5}$ after it underwent chemical transformation. For inert pollutants P' is equal to P . To account for the transportation effect, the integral over all receptors is solved, denoted by \mathbf{r} in the above equation, as the level of concentration of the pollutant under investigation, $c_{P'}$ depends on the receptor location and its density $\delta(\mathbf{r})$, e.g. in terms

of local population, depending on γ . The slope of the respective CRF in \mathbf{r} given as $[(\text{cases/a})/(\text{receptors } (\mu\text{g}/\text{m}^3))]$ is denoted by $m^{(\gamma, P')}(\mathbf{r})$.

Usually, $c_{P'}$ is measured in concentration change due to a change in the amount of emission. Commonly, the concentration level $c_{P'}(\mathbf{r}, e_{K,T,P}(\mathbf{x}))$ at a certain receptor – or cell when using grids for spatial representation – is determined using computationally intensive air quality models that model chemical and physical processes. Due to the large computing time this is not suitable in the context of assessing several different scenarios, not to mention in the context of an optimization approach. Thus, a common replacement is done as follows

$$c_{P'}(\mathbf{r}, e_{R,K,T,P}(\mathbf{x}^*, \zeta)) \approx \sum_{\tilde{r}} e_{R,K,T,P}(\mathbf{x}^*, \zeta) \tilde{c}_{P,P'}^{R,\tilde{r}} \quad (2-15)$$

where

$c_{P'}$ is the estimated change in concentration of pollutant P' ,

$e_{R,K,T,P}$ is the total emission of precursor P released due to activity of (K, T) in region R under the given scenario, and

\tilde{r} is the approximate location of the receptor location \mathbf{r} ,

$\tilde{c}_{P,P'}^{R,\tilde{r}}$ is the approximate unit change in concentration of pollutant P' at receptor \tilde{r} due to unit emission change of precursor P originating in source region R .

As a result one can use the approximation in eq. (2-15) and rewrite the integral from eq. (2-14) into the following sum

$$\tilde{I}_{K,T,P}^{(\gamma, P')}(\mathbf{x}^*, \zeta) = \sum_R \sum_{\tilde{r} \in \tilde{\mathbf{R}}} e_{R,K,T,P}(\mathbf{x}^*, \zeta) \tilde{c}_{P,P'}^{R,\tilde{r}} \delta(\tilde{r}) m^{(\gamma, P')}(\tilde{r}) \quad (2-16)$$

where

$\tilde{I}_{K,T,P}^{(\gamma, P')}$ is the approximate annual rate of impact γ due to exposure to P' , i.e. approximation of $I_{K,T,P}^{(\gamma, P')}$,

$e_{R,K,T,P}$ is the total emission of precursor P released due to activity of (K, T) in region R under the given scenario,

\tilde{r} is the location of a receptor,

$\delta(\mathbf{r})$ is the density of the receptor at location \mathbf{r} ,

$\tilde{c}_{P,P'}^{R,\tilde{r}}$ is the approximate unit change in concentration of pollutant P' at receptor \tilde{r} due to unit emission change of precursor P originating in source region R , and

$m^{(\gamma,P')}$ is the slope of the respective CRF.

In the context of this thesis a parametrized version of the original atmospheric dispersion model assuming linearity is applied. The assumption of linearity is not obligatory and could be changed in the equation. In fact, there are several other approaches that aim to preserve some of the non-linearity of the concentration formation of the original full-scale model by generating non-linear surrogate models (e.g. [Carnevale et al. \(2009, 2012a\)](#)). However, assuming linear or quasi-linear concentration changes in a marginal context is broadly accepted for the conditions at hand (c.f. [Krewitt et al. \(1998\)](#), [Bickel and Friedrich \(2005\)](#), [Tarrason \(2009\)](#), [Amann et al. \(2011\)](#), [Schwermer et al. \(2012\)](#)).

The special kind of linear surrogate model which is shown in eq. (2-15) makes use of source-receptor matrices. The change of concentration of pollutant P' at a receptor region \tilde{r} is determined by the emissions change of P in region R and is denoted by $\tilde{c}_{P,P'}^{R,\tilde{r}}$. It is assumed that the concentration change is linear in both (i) precursor pollutants P given that P is a precursor of P' , and (ii) source regions implying an additive effect of emissions changes from multiple sources R . Following [Starrett \(1994\)](#) non-marginal change is represented as a series of marginal changes, i.e. representing multiple policies as a consecutive effect of marginal changes.

Often more focus is set on receptor granularity, in the sense of finer spatial resolution of the receptors \tilde{r} , as opposed to more detailed representation of the source regions R . For European-wide or global assessment, it is common though to differentiate source regions at least on the national level (or sub-national level with several regions per country) and at the level of archetypical regions, for instance to distinguish urban from non-urban source regions. In this study source-receptor (SR) matrices are used which were determined from multiple runs of the EMEP model. The receptors are arranged in a grid having a 0.25 degree vertical (latitude) and 0.5 degree horizontal (longitude) resolution. This translates to a grid resolution of about 28 km \times 34 km over Berlin.

Note that linear impacts are assumed when assuming a linear CRF in eq. (2-14) by multiplying the term by $m^{(\gamma, P')}$ instead of making $m^{(\gamma, P')}$ a function of $c_{P'}$. Assuming linearity when assessing the relative risk for PM_{2.5} is considered valid over Europe (cf. WHO (2013a)). For other pollutants, like NO₂ for instance, threshold values may apply below which no harmful effect is expected (see Table 3-7 in chapter 3.4 for details). No threshold is assumed for PM_{2.5} as there is no evidence of a safe level below which no hazardous effects occur (WHO, 2013c; Spadaro and Rabl, 2008). At population level evidence for attributing health effects to certain chemical compositions of particles is too limited. Evidence for adverse health effects due to combustion-related particles is more consistent compared to other sources (WHO, 2013c; Stanek et al., 2011). The slope of $I_{K,T,P}^{(\gamma, P')}$'s CRF is the product of the background rate of disease (i.e. cases per year) multiplied by the relative risk above one (i.e. 6% for relative risk (RR) of 1.06, for instance).

As mentioned before, linearity for PM_{2.5} is probably invalid in highly polluted areas that exist in China or India, especially for the relative risk of mortality due to exposure to fine particles. In such cases, non-linear relationships have been proposed (e.g. Burnett et al. (2014)). To avoid non-linearity during optimization either a piecewise-linear approximation could be used similar to the approach described in chapter 2.4 or $c_p(\mathbf{r}, q)$ in eq. (2-14) should be replaced by several functions that are linearised near the background concentration levels present at \mathbf{r} .

Once, the impact $I_{K,T,P}^{(\gamma, P')}(\mathbf{x}, \zeta)$ in eq. (2-14) is determined one needs to aggregate the effects to come to an assessment of the overall impacts. The effects may occur over several health endpoints γ , but may also be incomparable. Therefore, a common unit via economic valuation is determined.

Without discussing the details here (see chapter 3.4.2 instead), it is assumed that the factor $\phi_{\gamma, \tau}$ is given that denotes the monetary value of one unit (or case) of γ at time τ . When WTP studies were used to determine $\phi_{\gamma, \tau}$ at time τ , an uplift factor from τ' to τ needs to be introduced which is used to estimate future WTP values at time τ' . The underlying justification for this approach is that with increasing wealth people would be willing to spend a higher amount of their income. In summary, the environmental costs

of conducting a unit of $a_{K,T}(\mathbf{x})$ for a given pollutant P is then determined by

$$\Phi_{K,T,P}(\mathbf{x}, \zeta) = \sum_{(\gamma, P')} \tilde{I}_{K,T,P}^{(\gamma, P')}(\mathbf{x}, \zeta) \phi_{\gamma, \tau} (1 + \Gamma_{\tau, \tau'})^{E(\tau' - \tau)} \quad (2-17)$$

where

$\Phi_{K,T,P}$ is the monetized environmental impact of conducting a unit of activity (K, T) for a given pollutant P ,

$\tilde{I}_{K,T,P}^{(\gamma, P')}$ is the approximate annual rate of impact γ due to exposure to P' ,

$\phi_{\gamma, \tau}$ is the monetary value of one unit (or case) of γ at time τ ,

E is the general income elasticity, and

Γ is the assumed growth rate of per-capita income from τ to τ' .

This allows to finally determine $D_{I,C}$ along with other terms in eq. (2-1).

2.3 Stochastic model formulation

In the previous chapter it was described how modal shifts as a response to policy intervention are dealt with in the proposed framework in a consistent scheme using identity equations. The model presented is deterministic. However, many of the parameters used are subject to uncertainty which may have a considerable effect on the outcome and, hence, on policy recommendations. In the deterministic case one may assume that each parameter enters the model with its expected value. The model has to be adjusted to be able to deal with a policy-maker's specific affinity to risk. Therefore, the objective function of a risk-neutral decision-maker may indeed be the maximisation of the expected net benefit while being aware and accepting an unknown level of uncertainty of the outcome. However, more risk-averse decision-makers may want to optimize the policy selection with the objective of maximizing the outcome under more unlikely but more severe and, hence, adverse events.

In the following the deterministic model formulation is extended to the stochastic case in

a fairly straightforward manner. The totality of all possible realisations of all stochastic parameters is denoted by $\hat{\Omega}$. Assume that one realisation of the stochastic parameters is given by a vector ω . Obviously, this vector is only one single possible realisation that occurs with a certain probability $P(\omega)$ and is part of a number of sampled scenarios $\Omega \subset \hat{\Omega}$.

To properly assess demand changes one needs to reformulate the deterministic version in eq. (2-9) and instead set

$$\pi_{K,T,Q,K',T'}(\mathbf{x}, \omega) = \begin{cases} t_{K,T}(\omega) \hat{a}_{K',T'}(\omega) \left[\left(\frac{x_{K,Q}}{\hat{x}_{K,Q}(\omega)} \right)^{\eta_{K,Q,K'}(\omega)} - 1 \right], & \text{if } \eta_{K,Q,K'}(\omega) > 0 \\ 0 & \text{otherwise} \end{cases} \quad (2-18)$$

and analogously adjust the estimated loss of surplus in eq. (2-11) and instead set

$$\begin{aligned} \Pi_{K',T',Q,K,T}(\mathbf{x}, \omega) &= \int_{\hat{x}_{K,Q}(\omega)}^{x_{K,Q}} \pi_{K,T,Q,K',T'}(\mathbf{x}, \omega) dx_{K,Q} \\ &= \int_{\hat{x}_{K,Q}(\omega)}^{x_{K,Q}^*} t_{K,T}(\omega) \hat{a}_{K',T'}(\omega) \left[\left(\frac{x_{K,Q}}{\hat{x}_{K,Q}(\omega)} \right)^{\eta_{K,Q,K'}(\omega)} - 1 \right] dx_{K,Q} \\ &= \left[t_{K,T}(\omega) \hat{a}_{K',T'}(\omega) x_{K,Q}^* \left(\frac{\left(\frac{x_{K,Q}}{\hat{x}_{K,Q}(\omega)} \right)^{\eta_{K,Q,K'}(\omega)}}{\eta_{K,Q,K'}(\omega) + 1} - 1 \right) \right]_{\hat{x}_{K,Q}(\omega)}^{x_{K,Q}} \end{aligned}$$

as well as adjust eq. (2-12) to

$$s_{K,T,Q,K',T'}(\mathbf{x}^*, \omega) = \sum_{q \in Q^{(p)}} \pi_{K,T,Q,K',T'}(\mathbf{x}^*, \omega) (\hat{x}_{K',q}(\omega) - \hat{x}_{K,q}(\omega)) \quad (2-19)$$

With respect to technological options uncertainty mainly arises due to two parameters, namely the reduction potential and the implementation cost: The reduction potential is given by the uncertain emission factor $f_{K,T,P}(\omega)$ which renders the emission estimate $e_{K,T,P}(\mathbf{x}, \zeta, \omega)$ for a given scenario (\mathbf{x}, ζ) uncertain. Additionally, the annuity $A_{K,M}(\omega)$ is uncertain due to its parameters being uncertain (cf. eq (2-7)): The investment cost $\kappa_{M,I}(\omega)$ of measure M at the beginning of implementation as well as its operational cost $\kappa_{M,O}(\omega)$. Huge influence on the range of the annuity is also due to uncertain discount rate r and unknown period of application n_M . It is generally recommended to use fixed values

for r and n_M and rather conduct a sensitivity analysis focusing on these two parameters as opposed to incorporating their uncertainty in the optimization problem. The influence of these parameters is discussed in chapter 7.3.

One may observe that the basic reference variables depend on ω , i.e. the specific realisation. This include the specific realisation of the cross-elasticities, $\eta_{K,Q,K'}(\omega)$, which was determined via an extensive literature review and a subsequent meta-regression analysis. This is described in more detail in chapter 4.

In a similar manner the equations dealing with the assessment of environmental impacts have to be adjusted. Impact estimation in eq. (2-16) changes to

$$\tilde{I}_{K,T,P}^{(\gamma,P')}(\mathbf{x}^*, \zeta, \omega) = \sum_{\tilde{r} \in \tilde{\mathbf{R}}} e_{R,K,T,P}(\mathbf{x}^*, \zeta, \omega) \tilde{c}_{P,P'}^{R,\tilde{r}}(\omega) \delta(\tilde{r}, \omega) m^{(\gamma,P')}(\tilde{r}, \omega) \quad (2-20)$$

and analogously the monetization in eq. (2-17) has to be rewritten to

$$\Phi_{K,T,P}(\mathbf{x}^*, \zeta, \omega) = \sum_{(\gamma,P')} \tilde{I}_{K,T,P}^{(\gamma,P')}(\mathbf{x}^*, \zeta, \omega) \phi_{\gamma,\tau}(\omega) \left(1 + \Gamma(\omega)\right)^{E(\omega)(\tau' - \tau)} \quad (2-21)$$

This formulation opens up a number of possibilities with respect to adjusting the objective function according to the risk-attitudes of a decision-maker. This is an advantage over the common deterministic formulation and will be discussed in chapter 2.5.2.

2.4 Piecewise-linear approximation of non-linear terms

In the previous sections the representation of policy interventions by using cross-elasticities to properly represent people's response to them was described. As mentioned earlier, one advantage of this representation is that the response can be modelled more realistically in a non-linear fashion. However, this comes at the expense of huge computing time. This limitation may render the chosen formulation infeasible as, in fact, the problem size increases drastically when the stochastic version of the model is applied.

It is proposed in the following to address this issue by separable programming. This will enable the approximation of non-linear terms of the original problem formulation by using

piece-wise linear approximation (PLA). This approach is applied to the terms described in chapter 2.2.2, so namely activity shift and utility loss for all values for which there is a cross-elasticity $\eta_{K,Q,K'} \neq 0$ defined which means they are affected by policy intervention.

Consider $\pi_{K,T,Q,K',T'}$ as an example here, as the others are determined analogously. The amount of activity shifted from (K, T) to (K', T') if the price component Q changes by a factor of $\tilde{\chi}_j$ relatively to its reference level $\hat{x}_{K,T,Q}$ is denoted by $\tilde{\pi}_{K,T,Q,K',T'}^{(j)}$.

The approach developed will make use of the χ -values by applying PLA between a fixed number of predefined price levels for components in Q . The relative price levels are in the following denoted by $\chi_{K,T}$. Obviously, one can come up with a set of m predefined relative price levels $\tilde{\chi}_1, \dots, \tilde{\chi}_m \in \tilde{\chi}$. Note, that these predefined levels can be specific to any characteristic of the absolute price level, but assume for the sake of simplicity and without loss of generality that a single set $\tilde{\chi}$ is used throughout the problem definition. In fact, optimal values can be found for a given number m of predefined values. Here, optimal is meant in a way that the aim is to minimize the effect of using a piece-wise linear approximation of the non-linear function as opposed to using the non-linear function directly in the optimization approach. This is a rather trivial individual optimization problem which minimizes the distance between the original function and the approximation for a predefined m . The reader is referred for instance to [Imamoto and Tang \(2008\)](#) which applies the methodology, though in a different context.

Consider again $\pi_{K,T,Q,K',T'}$ as an example. In fact, the function is parametrized by m values $\tilde{\pi}_{K,T,Q,K',T'}^{(j)}$ for $j = 1, \dots, m$. For each of the predefined relative cost component values $\tilde{\chi}_j$ the absolute cost component value is determined by setting $\tilde{x}_{K,Q}^{(j)} := \tilde{\chi}_j \hat{x}_{K,Q}$. The important benefit is that one can calculate the effect of policy intervention prior to optimization and can still make use of the non-linear term at the predefined levels $\tilde{\chi}_j$. For this reason, the methodology of PLA is used in similar contexts, e.g. in energy system models ([Loulou, 2008](#)). Interpolation takes place between two adjacent values $\tilde{\pi}_{K,T,Q,K',T'}^{(j)}$ and $\tilde{\pi}_{K,T,Q,K',T'}^{(j+1)}$ if the cost is between two adjacent values, i.e. if $x_{K,Q}$ is on the interval $[\tilde{x}_{K,Q}^{(j)}; \tilde{x}_{K,Q}^{(j+1)}]$.

The following must hold $\forall(K, Q)$ for the PLA being applicable:

$$\sum_{j=1}^m \lambda_{K,Q}^{(j)} = 1, \quad 0 \leq \lambda_{K,Q}^{(j)} \leq 1 \quad (2-22)$$

$$\lambda_{K,Q}^{(j)} = 1 \implies \forall j' \neq j : \lambda_{K,Q}^{(j')} = 0 \quad (2-23)$$

$$\exists \lambda_{K,Q}^{(j)} : 0 < \lambda_{K,Q}^{(j)} < 1 \implies \exists ! d \in \{-1, 1\} : \lambda_{K,Q}^{(j+d)} = 1 - \lambda_{K,Q}^{(j)} \quad (2-24)$$

$$x_{K,Q}(\lambda) = \sum_{j=1}^m \lambda_{K,Q}^{(j)} \tilde{x}_{K,Q}^{(j)} \quad (2-25)$$

$$\pi_{K,T,Q,K',T'}(\lambda) = \sum_{j=1}^m \lambda_{K,Q}^{(j)} \tilde{\pi}_{K,T,Q,K',T'}^{(j)} \quad (2-26)$$

$$\Pi_{K,T,Q,K',T'}(\lambda) = \sum_{j=1}^m \lambda_{K,Q}^{(j)} \tilde{\Pi}_{K,T,Q,K',T'}^{(j)} \quad (2-27)$$

where

$\lambda_{K,Q}^{(j)}$ is an independent variable and vector element of λ ,

$\tilde{x}_{K,Q}^{(j)}$ is a sampling point of $x_{K,Q}$ at interval index j ,

$\tilde{\pi}_{K,T,Q,K',T'}^{(j)}$ is the value of $\pi_{K,T,Q,K',T'}$ at interval index j , and

$\tilde{\Pi}_{K,T,Q,K',T'}^{(j)}$ is the value of $\Pi_{K,T,Q,K',T'}$ at interval index j .

In fact, the optimization problem changes as not the cost values $x_{K,Q}$ – elements of \mathbf{x} – are optimized directly but instead an optimal solution with respect to values $\lambda_{K,Q}^{(j)}$ being vector elements of λ is determined. To account for the requirements of the adjusted optimization problem, eq. (2-22)- (2-24) are necessary due to the following reasons: By applying PLA, the problem is transformed from a continuous Non-Linear Problem (NLP) into a linear Mixed Integer Problem (MIP). The MIP formulation is required because the solution process needs to impose (i) an adjacency restriction, and (ii) a restrictions that no more than two values can be non-zero as enforced by the above equations. Therefore, solvers implicitly define an additional set of variables called a special ordered set (SOS).

An SOS is an organized set of variables used to specify the aforementioned restrictions in an optimization model, namely adjacency and at most two non-zero values. The member elements of a SOS in this case are continuous variables equal or larger than 0 and smaller

or equal to 1. The problem itself containing the SOS becomes an MIP. The restrictions state that at most two weights are positive and if two weights are positive (not only one) then they have to be adjacent.

2.5 Representing risk attitudes in the objective function

It was shown in chapter 1.4 that related work commonly ignores the impact of uncertainties of the overall result when conducting policy optimization to derive cost-effective or cost-efficient strategies. Consequently, the objective of maximizing total net benefit is commonly done by use of best guesses or mean values of variables. The uncertainty of the recommended policies is then appreciated afterwards by rough assessment of the uncertainties of avoided external impacts (e.g. using figures from [Holland \(2014\)](#)). Therefore, such approaches cannot account for risk attitudes during the optimization but will always determine a risk-neutral result. To cope with this issue to a limited extent, some approaches deliberately over-estimate control costs or exclude uncertain parts of the assessments entirely from the analysis (cf. [Amann et al. \(2011\)](#)) Obviously, such approaches produce biased results. The fundamentally different approach in this thesis incorporates uncertainty in a stochastic optimization approach and appreciates risk affinity in the objective function.

To stress the importance of this difference let us, for the sake of simplicity, consider an isolated example: It will be shown in chapter 4 that people in the Netherlands seem to be responsive to fuel taxation, though only moderate, with a mean increase of 0.12% in public transport demand per 1% increase in fuel price, i.e. one may expect a moderate decrease in overall demand for small increases of fuel price. However, the response is uncertain on a 95% confidence interval (CI) from -0.04 to 0.25. Thus, in the worst case an increase in fuel tax may provoke the undesired response of even slightly increased overall car travel. While this may sound irrational, this reaction of car travellers has been observed in several studies. Initially, an increased fuel price may reduce the number of participants of individual travel. Less vehicles result in temporarily improved driving conditions,

e.g. due to less congestion. However, this makes individual motorized transport more attractive which may result in increased travel of the remaining participants potentially increasing total travel demand. However, when ignoring ranges and incorporating the expected value or best guess only ($\eta = 0.12$) during the assessment a fuel tax will provoke reduction in car travel demand if it is cost-efficient at that single value only.

For exemplary purposes, consider risk to be an increase in pollution levels only leaving utility losses aside. Then, considering above example, for a decision-maker that aims to avoid risk in the form of increased externalities due to higher levels of car travel, an increase of fuel tax as policy instrument is not an option. However, a risk-neutral policy-maker may judge the situation differently as in the majority of cases car travel demand will decrease after policy implementation and the risk of increased pollution after tax raises is low. Hence, a differentiation of the decision-maker's risk attitude is imperative when the aim is to properly integrate probabilities in the optimization approach and derive meaningful insights for policy making.

2.5.1 Existing approaches to measure risk of decisions

The selection of policies and their interaction under uncertain conditions and uncertain impacts has similarities with portfolio optimization. Modern portfolio theory (MPT) is considered to have commenced with the work of [Markowitz \(1952\)](#). The mean-variance analysis approach postulated by MPT aims for compiling a portfolio of assets such that the expected return (or expected gain) is maximized for a given level of risk. Risk is defined as variance which has several shortcomings to be discussed later. In MPT the gain or risk of an asset is not assessed by the gain or risk of the individual asset but instead by its contribution of the overall return and risk.

MPT is concerned about stock market investors – i.e. decision-makers or policy-makers in the context of this thesis – that aim to combine assets – i.e. policy instruments – to portfolios – i.e. bundles of policies. The return of a portfolio, say the net benefit for society in policy-making, is the proportionally weighted combination of the expected returns of the assets that constitute the portfolio. The risk of a portfolio is measured by its return variance and MPT assumes in general that investors are risk-averse, that is

they chose from two portfolios with same expected return the one that is considered less risky than the other. So, in general, for an investor to decide to chose a portfolio with higher variance (i.e. higher risk), it has to have higher expected return. More specifically, an investor decides based on the portfolio's risk-return trade-off.

Several proposals exist on how to incorporate the risk into the return estimate of a portfolio by building a risk-adjusted return of an asset and a portfolio. For instance, the so-called Sharpe index being the reward-to-variability ratio (Sharpe, 1966, 1994) or the Sortino ratio scoring a portfolio's risk-adjusted return relative to an investment target (Sortino and Price, 1994). Today, different approaches exist in portfolio optimization that measure risk differently. The traditional mean-variance measures risk based on a portfolio's standard deviation of return or its squared standard deviation of return, i.e. its variance. While being a classical textbook example it is not considered a robust risk measure to base decisions on.

Modern conceptions of risk attitude in decision making (and optimization) under uncertainty distinguish between risk-averse, risk-neutral and risk-seeking attitudes of decision-makers. Basically, this is a characterization of how a person reacts in scenarios of the same expected return but facing one scenario with guaranteed pay-off and the other one without. A person is considered to be risk-averse, i.e. the person avoids risk, if the person would accept a certain return below the expected gain rather than deciding for a risky scenario with higher expected return. In that person's view gambling should be avoided. The accepted lower but guaranteed pay-off is called the certainty equivalent. The minimum amount by which the expected return of a risky portfolio must exceed the risk-free one is called the *risk premium* and can be understood as the minimum compensation to make the investor indifferent between the scenario, so to make the investor also be willing to decide for a risky portfolio. If a person is indifferent to risk, i.e. if the person has no preference of a risk-free scenario over a gambling scenario of the same expected return and vice versa, the behaviour is labelled risk-neutral. A risk-seeking or risk-affine person, however, would accept a more risky portfolio even if the expected value of a risk-free scenario is higher. This implies a negative risk premium.

Expected utility theory is concerned with decision-makers' preferences about choices that exhibit uncertain return as described above. A concept to incorporate this is the Arrow-

Pratt measure of a decision-maker's absolute and relative risk aversion (Pratt, 1964). Absolute risk aversion (ARA) measures the risk aversion $A(w)$ by building the negative ratio of the second derivative and the first derivative of a decision-maker's utility function, i.e. $A(w) = -u''(w)/u'(w)$ for a utility function $u(w)$ in which w is wealth, i.e. the variable the decision-maker prefers more of. A positive value implies risk-aversion while a negative ARA characterizes risk-affine decision-makers. In principal, the measure can be used to compare the level of risk-aversion of two decision-makers given that their individual utility functions are known. If ARA is constant, the decision-maker shows constant absolute risk aversion (CARA). However, it is often found in empirical studies and experiments that a more realistic representation would be decreasing absolute risk aversion (DARA) instead. It is observed that people often become less risk-averse with increasing initial wealth or by mistakenly treating consecutive probabilities in an isolated manner. Another observation is that people tend to reverse their attitude towards risk after they experienced gains or losses (reflection effect). There is another variant of the Arrow-Pratt measure which measures risk aversion in relative terms as opposed to absolute values: Relative risk aversion (RRA) is defined as the product of the ARA function and wealth w , so $R(w) = w A(w)$. The measure can be used when the aforementioned effect occurs, i.e. when the utility function may change from risk-avoidance to risk-seeking when wealth increases or decreases.

Opposed to the assumption that people base their decision in relation to the final outcome, prospect theory assumes that individuals base their decision on a heuristic evaluation of potential gains and losses (Kahneman and Tversky, 1979). The theory is founded in behavioural economics and the theory can be used to model the choice of individuals between probabilistic alternatives where these alternatives are associated with risk. It has been shown by Tversky and Kahneman (1992) that individuals are to a higher degree psychologically influenced by losses as opposed to gains of the same size.

Until today, several other metrics of risk emerged in different fields of economics and several coherent risk measures were developed to quantify these metrics. The choice of metrics to account for the specifics of the problem at hand are discussed in the next section.

2.5.2 Objective function under specific risk attitude

As mentioned in the previous section people tend to show risk-averse behaviour, especially when high losses are at stake. Generally, they tend to over-value potential losses compared to potential gains (Tversky and Kahneman, 1992). In the context of policy making in which a decision influences mostly others, and especially when these others might have the power to end the policy-maker's election term, that decision-maker is likely to avoid losses. This is the case because adverse outcomes of a policy decision may be judged by the general public as a lack of governance. Therefore, proper risk measures should be utilized. In the following the value-at-risk (VaR) and conditional value-at-risk (CVaR) will be investigated in more detail and their application in the context at hand will be described.

Commonly, VaR is used in financial risk management. In the original context the random variable is concerned with loss, in particular with the loss of a given portfolio. For this portfolio and a given probability θ , the θ -VaR is defined as the loss value z such that the probability of the loss on the portfolio exceeding z is θ . In other words, if a portfolio has a 5% VaR of 10 € million, this describes the presence of a $\theta = 0.05$ probability that the portfolio will fall in value by $z = 10$ € million or more. One big disadvantage of the use of VaR is that it does not control any scenarios in which the loss exceeds z . Recall that the shape of the distribution of $Z(\lambda, \zeta, \omega)$ is determined by the bundle of policies, i.e. by λ and ζ . As a consequence the selection and parametrization of policies for a given θ and for a resulting total net benefit $Z(\lambda, \zeta, \omega)$ may be chosen in a way that values beyond the VaR are part of a undesirably shaped distribution tail. To overcome this issue the CVaR will be introduced which is concerned with the expected value in the worst cases. This corresponds to the expected value when only looking at the part of the distribution below a certain value, namely the VaR. In the context at hand total net benefits are considered instead of losses. Still, the focus is on the left tail of the distribution of $Z(\lambda, \zeta, \omega)$, i.e. the worst cases of the outcomes under the recommended policy parametrised by λ and ζ . Thus, only the expected value in the left tail of the distribution of $Z(\lambda, \zeta, \omega)$ is considered:

$$\mathbf{CVaR}_\theta \left[Z(\lambda, \zeta, \omega) \right] = \mathbf{E} \left[Z | Z < \mathbf{VaR}_\theta \left[Z(\lambda, \zeta, \omega) \right] \right] \quad (2-28)$$

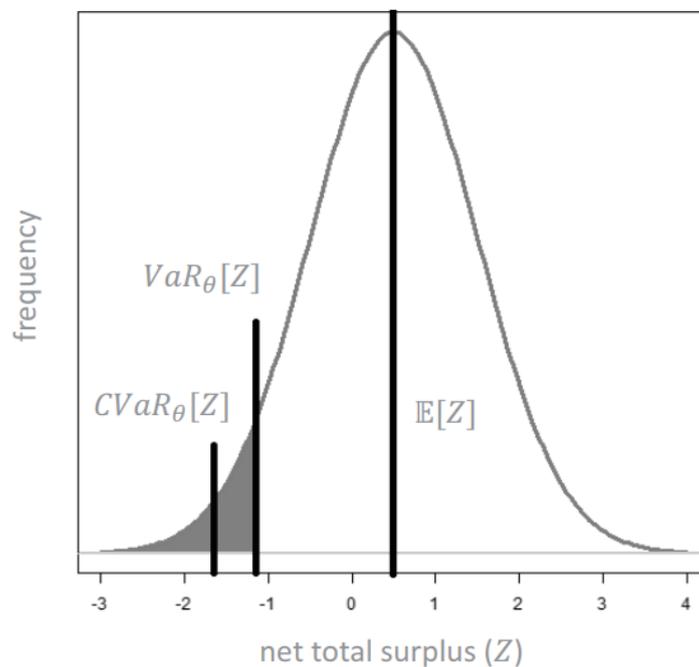


Figure 2-1: A stylised distribution of net benefit. For the specific distribution the expected value, value-at risk, and conditional value-at risk are indicated. It is important to recognize that the distribution of net benefit itself depends on the policy selection and, hence, on the objective function.

By considering all values of the left tail of the distribution of the total net benefit $Z(\lambda, \zeta, \omega)$, CVaR accounts for the worst case values specifically as opposed to only a threshold value like the VaR.

A decision-maker's attitude towards risk is likely to have considerable influence on policy selection and parametrization. Figure 2-1 shows a stylised distribution of net benefit and indicates the individual levels of VaR, CVaR, and expected value (EV). It is, however, important to further recognize that the distribution itself depends on the policy selection. So, if a risk-averse decision-maker decides to set out the objective to minimize the risk of net loss due to policy implementation he will aim to maximize the expected shortfall, i.e. the CVaR. A risk-neutral decision-maker will aim to maximize the net benefit under expected conditions and, hence, will set out the objective to maximize the EV of the net benefit.

In this section an approach is proposed to deal with different levels of risk aversion based on the described stochastic formulation (see chapter 2.3). In contrast to the objective function in the deterministic case that aims to maximize the expected net benefit (see chapter 2.2.1), objective functions are proposed in the following that deal with the net benefit to be expected in the worst cases.

The function of net benefit in the stochastic case and adjusted to the PLA approach can be written as

$$Z(\lambda, \zeta, \omega) = \sum_{I,C} D_{I,C}(\lambda, \zeta, \omega) - L_{I,C}(\lambda, \omega) - S_{I,C}(\lambda, \zeta, \omega) \quad (2-29)$$

under constraints eq. (2-22) to eq. (2-27) to ensure PLA conditions, where

$D_{I,C}(\lambda, \zeta, \omega)$ is the amount of avoided damages (externalities) caused by activities conducted by members of I in country C under scenario ω and policies (λ, ζ) ,

$L_{I,C}(\lambda, \zeta, \omega)$ is the reduction in additional utility that affects members of group I in country C under scenario ω and policies (λ, ζ) , and

$S_{I,C}(\lambda, \zeta, \omega)$ is the total cost to be spent by society to support policy intervention affecting members of group I in country C under scenario ω and policies (λ, ζ) .

A risk-neutral decision-maker would choose the policy scenario that maximizes net benefit under expected realisation of parameters, i.e.

$$\max_{\lambda, \zeta} \mathbf{E} \left[Z(\lambda, \zeta, \omega) \right] \quad (2-30)$$

given constraints eq. (2-22) to eq. (2-27). A more risk-averse decision-maker may instead favour to maximize the left tail of the distribution of the expected total net benefit. For a given value of θ one can set the objective function to

$$\max_{\lambda, \zeta} \mathbf{CVaR}_\theta \left[Z(\lambda, \zeta, \omega) \right] = \mathbf{E} \left[Z | Z < \mathbf{VaR}_\theta \left[Z(\lambda, \zeta, \omega) \right] \right] \quad (2-31)$$

given constraints eq. (2-22) to eq. (2-27). The \mathbf{VaR}_θ is a measure of the risk of investment at probability θ , so by $\theta \in [0; 1]$ the threshold loss value is denoted, i.e. the probability at which the net benefit is below the value at risk. The expected value beyond this level is given by the conditional value at risk, i.e. by \mathbf{CVaR}_θ .

Another option is to trade-off the aforementioned measures using a parameter $\phi \in [0; 1]$. So for a given ϕ and θ one optimizes for

$$\max_{\lambda, \zeta} \left(\phi \mathbf{E} \left[Z(\lambda, \zeta, \omega) \right] + (1 - \phi) \mathbf{CVaR}_\theta \left[Z(\lambda, \zeta, \omega) \right] \right) \quad (2-32)$$

given constraints eq. (2-22) to eq. (2-27).

The decision-maker needs to select values for ϕ and θ or may want to determine the results for different settings of the two parameters. The choice of θ is related to the sample size given that the optimization problem cannot be solved analytically (cf. chapter 6). Usually, values for θ are small as it deals with the worst cases which should be considerably lower than the total number of scenarios analysed. Reasonable values depend on the sample size and may range from $\theta = 0.2$ for smaller sample sizes to $\theta \leq 0.05$ for a very large set of samples. A sensitivity analysis for ϕ is conducted in chapter 6.4 to determine the influence of risk-aversion on policy recommendation.

Part II

Case study

3 Environmental data and their uncertainty

This chapter deals with the data necessary to determine avoided impacts after policy implementation. The respective assessment process is formalized in chapter 2.2.3. As aforementioned these estimates are subject to uncertainty. Quantification of the uncertainty of the data collected in this step is particularly challenging. Consider the impact of air pollution as an example: Impacts from air pollution derived by applying the Impact Pathway Approach (IPA) are subject to uncertainty as the process combines data from different sources including estimates of changed ambient air concentrations and the relationship to health outcomes. Furthermore, each of the individual sources is subject to uncertainty itself which propagates through the full chain approach of the IPA. In the following the uncertainties along the IPA are analysed and quantified where possible. Thus, this chapter is organized as follows:

In chapter 3.1 reference activity levels are discussed. Furthermore, two models are developed dealing with association of activities to socio-economic groups. Afterwards, emission factors (EFs) and their uncertainties are presented in chapter 3.2. Several sources of uncertainty play a role when assessing the effect of reduced amounts of emission on air quality levels. Thus, these sources are addressed in chapter 3.3.

Furthermore, there is considerable uncertainty when modelling the relationship between exposure to harmful substances and respective responses, e.g. in health effects, as well as their economic valuation. These effects are quantified and discussed in chapter 3.4. The uncertainty of the impact of climate change as well as its monetization is discussed in chapter 3.5.

3.1 Reference demand and activity levels

3.1.1 Basic reference activity

The basic reference activity (or demand) data used in this work is output of the TREMOVE model (TML, 2007). The most recent publicly available version is used (Version 3.3.2).

In terms of demand, the model provides demand data, occupancy rates, load factors per country, trip purpose, trip distance, region, period, network, vehicle category, fuel type, vehicle type and year. In terms of stock, the data are stratified per country, vehicle category, fuel type, vehicle type, vehicle technology, vehicle age and year.

The reference demand for the year 2030 is given in Figure 3-1. The distinction into urban and non-urban regions is extended: It is assumed that 20% of person-kilometres (PKMs) driven on urban roads can be attributed to an urban activity centre, a so-called central activity district (CAD).

The original data are not stratified by socio-economic group. As a result neither stock nor demand are associated with income groups as is needed for the purpose of this analysis. Therefore, two probabilistic models were developed and applied to (i) determine modal shares per income group by developing mode-specific Lorenz curves informed by travel survey data, and (ii) associate technology-specific activity data to socio-economic groups via stock age distribution. They are presented in more detail in chapters 3.1.2 and 3.1.3.

Uncertainty estimates with respect to the activity data are not available from TREMOVE. For reference scenarios, overall activities are an input to TREMOVE and are taken from the energy model PRIMES. For future estimates the main influence on the results is due to growth of population and economic development. [Kouridis et al. \(2011\)](#) conducts a sensitivity analysis and estimates uncertainty of TREMOVE results at about 3%. For general activity data, the European Environment Agency (EEA) suggests to apply error ranges of less than 2% if data are derived from national statistics and about 2-10% for data from the International Energy Agency (IEA) or from United Nations (UN) databases ([EEA, 2014c](#)). These suggestions are followed and a coefficient of variation of 5% is applied as the input data for future projections is based on national official statistics, assuming normal distribution.

Changes in demand per mode, i.e. the modal shift, are expressed in a common unit as PKM being moved from one mode of transport to another (cf. chapter 2). However, emission factors per technology-specific vehicle type are usually given per vehicle-kilometre (VKM) and, hence, need to be adjusted with mode-specific factors that are discussed in this section. A conversion between VKM and PKM is usually performed by applying occupancy rates specific to vehicle categories. Thus, the occupancy rate is an important

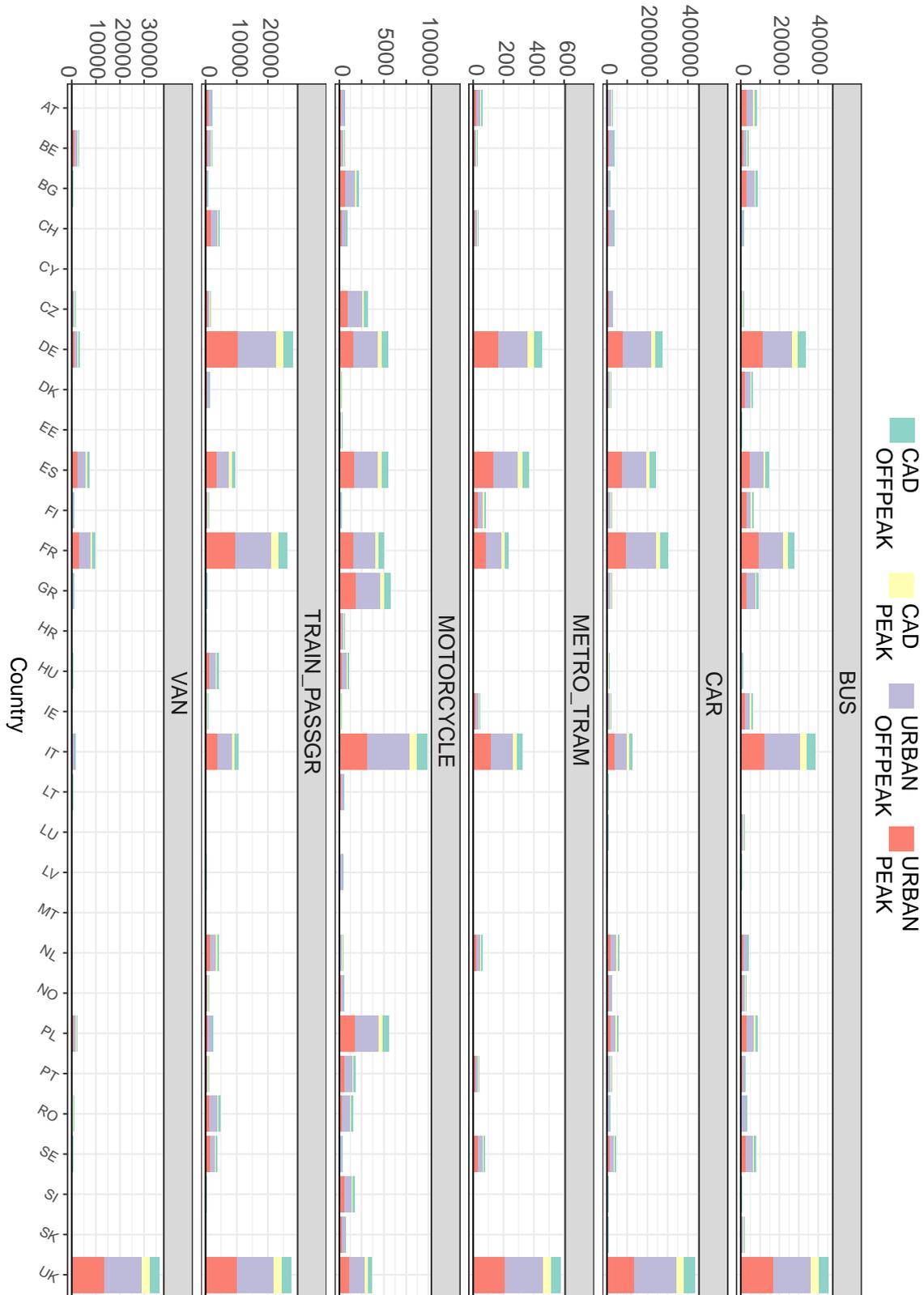


Figure 3-1: Projected reference demand [million PKM] of different vehicle categories in 2030. Figure shows peak vs. off-peak and central activity district vs. general urban area.

factor to be considered when estimating modal shifts and assessing their effects. Figure 3-2 shows the occupancy rates of cars, trains, metro or tram, and buses or coaches for the EU28+2 as derived from the TREMOVE model. Occupancy rates per passenger vehicle were also collected by EEA (2010) for cars, trains and buses. The data available are generally sparse but cover Western European countries along with Eastern European countries. It spans the years 2004 to 2008 with heterogeneous data availability per country and mode.

EEA (2010) finds car occupancy rates ranging from 1.5 to 1.6 for Germany, Switzerland,

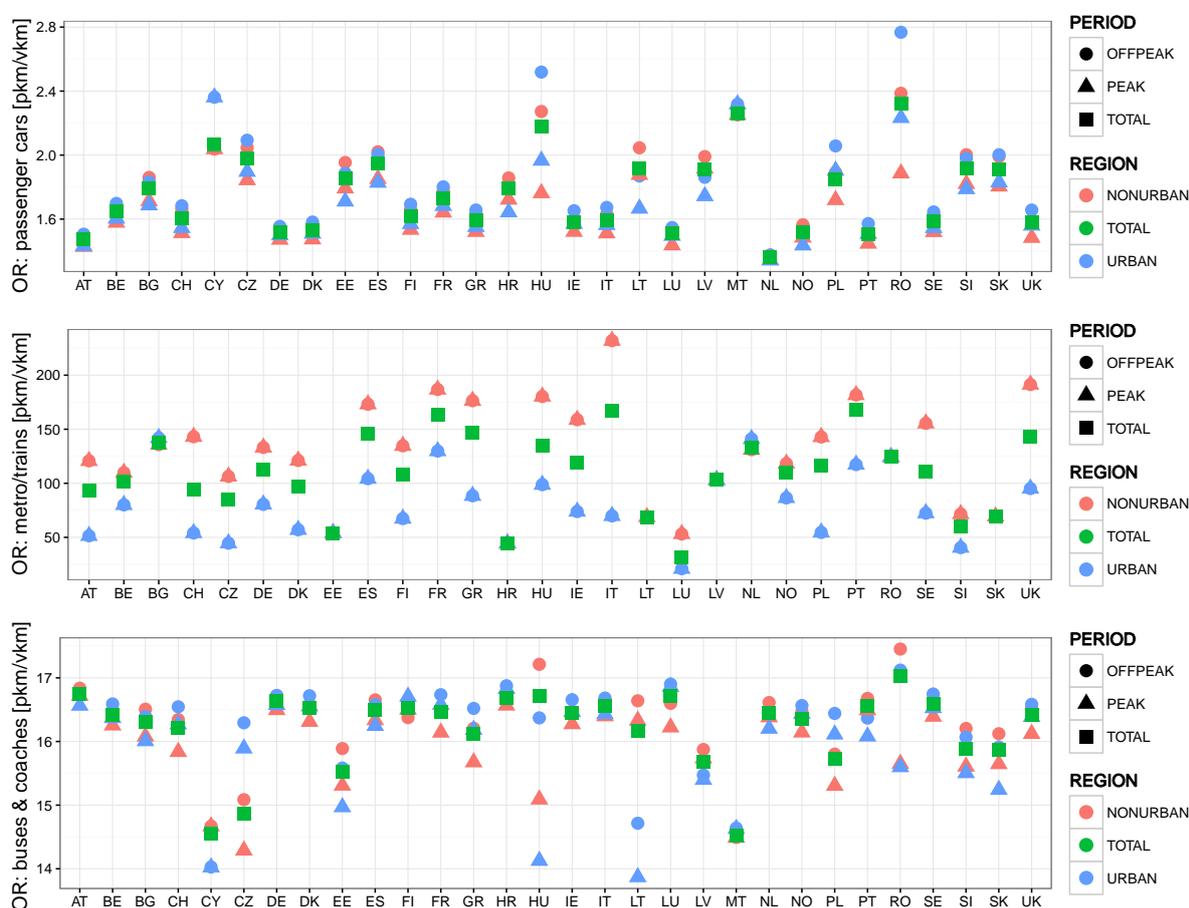


Figure 3-2: Occupancy rates (OR) of cars, trains/metro/tram and buses/coaches for European Union, Norway and Switzerland (EU28+2) as derived from the TREMOVE model. The data are distinguished by region and time of the day.

Denmark and the United Kingdom, slightly lower values of around 1.4 for the Netherlands, slightly higher values ranging from 1.6 to 1.7 for Norway, Spain and Italy and generally higher but slowly decreasing values of 1.8 to 2.0 for the Czech Republic, Slovakia and Hungary.

A similar pattern of higher occupancy rates in Eastern European countries and a stable value of around 1.5 to 1.7 in Western European countries can be observed in Figure 3-2. With increasing car ownership the occupancy rates in Eastern European countries is expected to fall. Such a development could be observed in Europe with rates falling from around 2.0 in the early 1970s to today's levels in the early 1990s.

In the same period car ownership in EU member states rose substantially from 181 in 1970 to 428 in 1995 (Banister, 2000). For on-road public passenger transport the data are compared to findings of Özdemir (2012) who assumes 14 PKM/VKM for public (urban) buses and 23 PKM/VKM for coaches based on Brosthaus et al. (2003). One observes that in the data used in this thesis no occupancy rate higher than 18 PKM/VKM is reached. Also, the difference between urban buses and long-distance coaches is less distinctive. Across all countries, PKM over VKM ratios for coaches and for urban buses both are about 16 to 17. For rail-bound public transport the majority ranges between 50 to 150 PKM/VKM (cf. Figure 3-2).

3.1.2 Development of mode-specific Lorenz curves

The goal of this chapter is to derive Lorenz curves for each transport mode and country based on country specifics like income distribution, quality of rail-bound traffic and motor vehicle availability. Multi-model inference techniques are utilized to reduce model selection bias when regressing model coefficients. Such bias can otherwise easily arise as a result of to data scarcity. This effect is often neglected in similar studies and leads to seemingly correct but obviously biased results.

Even though unequal mobility is recognized as an important issue in politics, in general, data collection efforts at national level are very limited and the availability of measures to reduce the social consequences of transport inequality are not studied sufficiently. There is insufficient travel survey data collected at European level but some individual

unharmonised efforts are made at different levels of detail and coherence on national level. There have been first efforts to collect information on European level about the individual national travel survey data in the OPTIMISM project ([Ahern et al., 2013](#)).

Many datasets are not publicly available. In many cases there is no link between socio-economics like personal or household income and the modal use of transport. Accessible data from national travel surveys are listed in Table 3-1.

For each transport mode, i.e. for passenger trains and metro/tram, cars/vans and buses, the aim is to determine the share of each income quintile with respect to the total PKM driven in this mode. Therefore, the level of disparity and inequality has to be determined. Income distribution is commonly measured with the so called Lorenz curve. The approach developed in this thesis aims to determine a similar distribution for each transport mode. This is a novel concept which has not been addressed before in this context.

It is required that the curve passes through both the origin and point (1, 1) as shown by function $L(r)$ in Figure 3-3. Also it has to be a monotonic function, i.e. its derivative is non-decreasing. The diagonal through the origin is called the line of perfect equality and would translate into shares of 0.2 each for the income quintiles.

Table 3-1: Travel surveys across Europe that served as data source to derive mode-specific Lorenz curves

Country	Name of the survey	Year(s)	Sample size
United Kingdom	National Travel Survey ^a	2006-2012	19,000 persons in 8,200 households ^b
Germany	Mobilität in Deutschland ^{c,d}	2008	60,713 persons in 25,922 households
Denmark	Danish National Travel Survey ^e	2000	20,000 persons ^f

^a [DfT \(2013\)](#) ^b in the 2012 survey ^c [infas and DLR \(2010\)](#) ^d Income data from [Statistisches Bundesamt \(2012\)](#) was needed to build an association of fine-grained income groups used in [infas and DLR \(2010\)](#) to income quintiles as used in this study.

^e [DTU \(2012\)](#) ^f Stated in the documentation for a typical year.

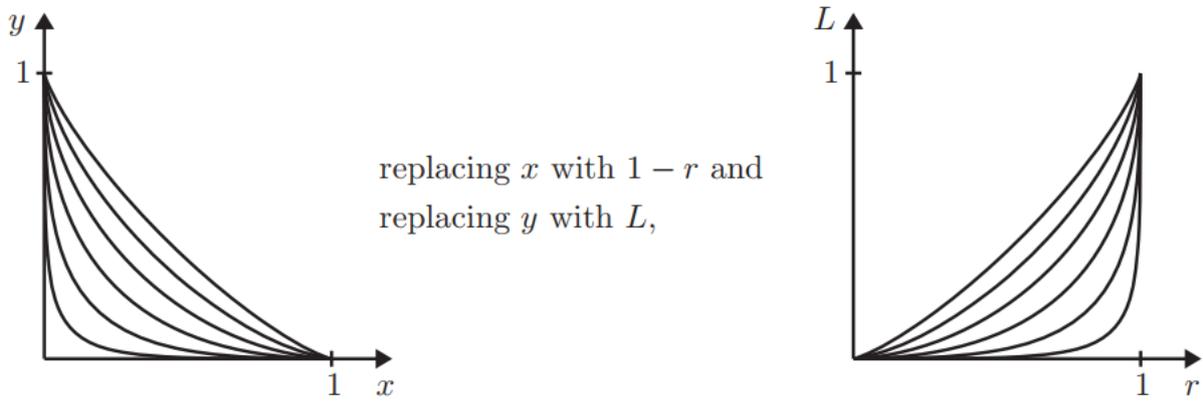


Figure 3-3: Lamé curves with $a = b = 1$ for various values of k (on the left) and function $L(r)$ after setting $L = y$ and $x = 1 - r$ (Source: Henle et al. (2008)).

The general Lorenz curve represents the proportion $L(r)$ of the income, where $0 < r < 1$ is the rank of an individual based on his or her level of the income in the whole population, e.g. a country. Even under these constraints the resulting number of functions is infinite. There have been some efforts to describe typical distributions with as little as one or two parameters. Henle et al. (2008) argue that the Lorenz curve is well-modelled by a single parameter k and the family of functions

$$\{L(r) = (1 - (1 - r)^k)^{\frac{1}{k}}\} \quad (3-1)$$

which is derived from the family of Lamé curves defined as

$$\left\{\left(\frac{x}{a}\right)^k + \left(\frac{y}{b}\right)^k = 1\right\} \quad (3-2)$$

for some real-valued parameters a and b . By setting $a = b = 1$ and $k < 1$, one determines

$$\{x^k + y^k = 1\}. \quad (3-3)$$

Typical shapes of these types of curves are displayed in Figure 3-3. By setting $L(r)$ as in eq. (3-1) the curves are forced to be fitted via k to distributions where the curve is below the line of equality (i.e. the diagonal), i.e. scenarios in which the richer individuals of a population own an over-proportionate amount of resources. In this context owning

more resources means travelling more in a specific mode. While this is a seemingly realistic constraint for the more comfortable individual modes of traffic like cars, this is too restrictive and thus unrealistic when looking for distributions of the less comfortable modes of transport. Thus, the model formulation was adjusted to allow for cases where the poor own a higher share of the 'resources' than the rich. This is a realistic scenario when the resource is a less comfortable, hence, less desirable mode of transport. Therefore, for non-individual transport modes the formula of eq. (3-1) is adjusted as follows

$$\{L_{C,K}(\tau) = (1 - (1 - \tau)^{k_{C,K}})^{g_{C,K}}\} \quad (3-4)$$

where

$L_{C,K}$ is the estimated Lorenz curve of transport mode K in country C ,

τ is the share of income or wealth,

$k_{C,K}$ is a regression coefficient for the estimated Lorenz curve of transport mode K in country C , and

$g_{C,K}$ is a regression coefficient for the estimated Lorenz curve of transport mode K in country C .

For $g_{C,K} = 1/k_{C,K}$ this is representative for individual traffic. Note that the regression coefficients do not have a specific meaning but are only used to constrain the shape of $L_{C,K}$. The goal is to regress them when fitting transport mode distributions collected from the national travel survey data.

Afterwards, one determines country- and mode-specific factors $k_{C,K}$ and $g_{C,K}$ which will yield respective Lorenz curve like distributions $L_{C,K}$ for transport mode K in country C . It turns out that this serves its purpose well as shown in Figure 3-4.

As aforementioned, the scarcity of survey data makes a model that is fit by a single regression very likely to be over-fitted. One may choose from many subject-specific parameters like the number of motor vehicles per 1,000 inhabitants, quality of rail-bound transport services, general levels of income and its distribution, or any other measure that is available in transport statistics. Obviously, multiple models of the same family of functions do exist and can be modelled by building regression models for two dependent

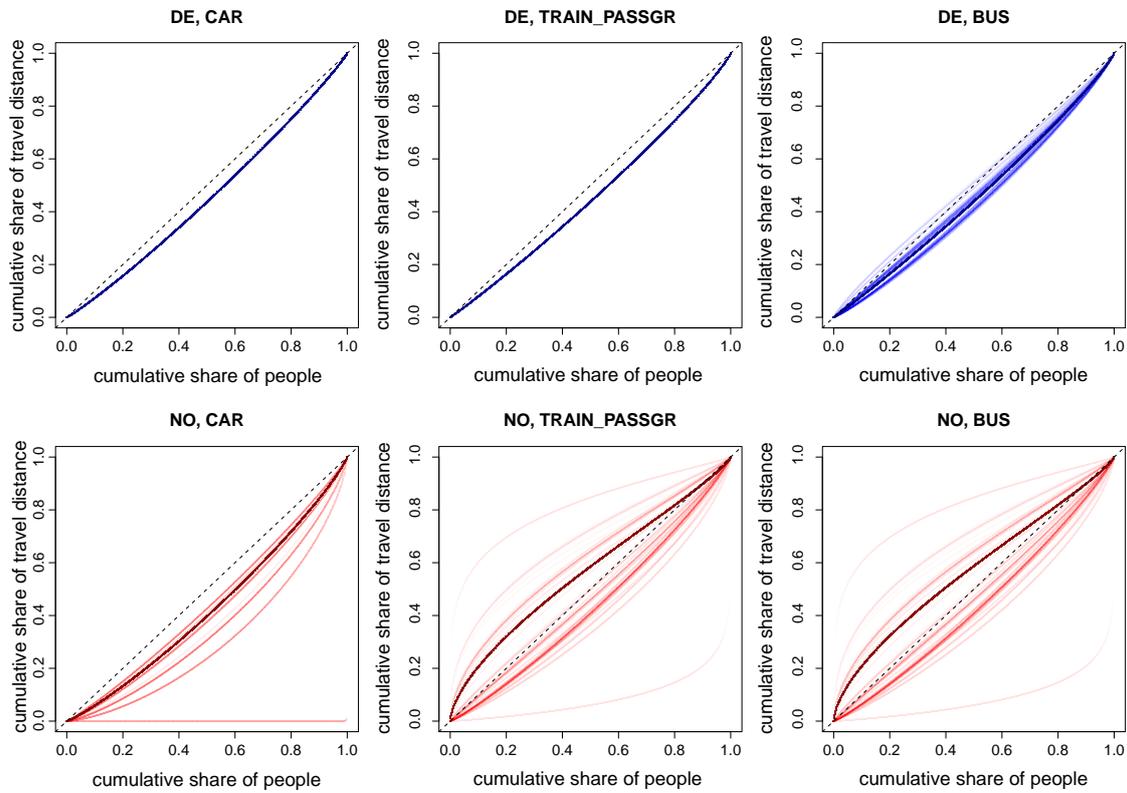


Figure 3-4: Lorenz curves derived via Bayesian model averaging (BMA) for three common modes of transport, namely cars, passenger trains and buses. The figures in the upper row show models for Germany (DE) and the figures in the lower row show models for Norway (NO). The dark-coloured line shows the expected curve derived via BMA and the light-coloured lines show the individual models whereas the alpha value indicates the probability of the individual model.

variables k and g that utilize the aforementioned parameters as their explanatory variables. Consider the following five predictors of which each is taken as the deviation of the EU mean for scaling purposes:

- Gross domestic product (GDP) at purchasing power parity (PPP) per capita
- Gini index, i.e. the income or wealth distribution of the residents of a nation
- Rail track density
- Motor vehicles per 1,000 people

- Population density

While the structure of this model may be postulated by knowledge about the transport sector of a country the model chosen from a set of candidate models is usually the one considered best based on its fit to the data. This is called model selection. For simple regression models this is about the same as variable selection. However, standard variable selection methods may result in models that are poor in terms of their inferential properties (Freedman, 1983; Lukacs et al., 2010). Models derived from these standard techniques may be especially poor in the aforementioned sense when the possible models, i.e. possible parameter combinations, are large and, hence, the number of models may be of the same order of magnitude as the sample size (Lukacs et al., 2010). Still the methodology is commonly applied in many disciplines and the models are presented as proper and the dependent variables are considered as important and explanatory (due to high t -values) while they might, in fact, be arbitrary choices. This misconception of considering false positives is captured in the so called 'Freedman's paradox'. The effect described in Freedman (1983) is a result of an extreme case of model selection bias. Situations arise in which 'explanatory' variables with no connection to the response variable may commonly and spuriously inflate R^2 . When choosing the seemingly best model, thereby ignoring other models, one discards valuable information due to the belief that a weak relationship of one or more variables with the response renders a model insignificant. Selecting a single model may be misleading and is indifferent to the selection method applied. There is little that can be done to overcome the adverse effects of selection bias (Lukacs et al., 2010; Miller, 2002).

For a single model all inference is conditional on the selection which usually is biased and uncertain. However, a possibility is to completely avoid the selection of a single model but keep a collection of non-redundant models instead and infer results from multiple models at once.

A common method applied in this context is model averaging, in particular BMA. The general concept as applied to the context of Lorenz curves is outlined in the following. The reader is referred to Hoeting et al. (1999) for the general review and a more detailed mathematical formulation.

Given a collection of travel surveys the aim is to determine the distributions $L_{C,K}$ for

transport mode K in country C (cf. eq. (3-4)). Therefore, the curve parameters $k_{C,K}$ and $g_{C,K}$ are of particular interest. Consider several regression models M_1, M_2, \dots, M_N . As described before five potential predictors are investigated. Even when considering only regression models without interaction of predictors one may already determine 2^5 models. Obviously, variable interactions will tremendously increase the number of models.

When applying BMA the focus is on the probability of each of the individual regression models for the two parameters and how it is utilized to build a weighted average across the models. By the law of total probability the posterior distribution of $k_{C,K}$ is a weighted average of $k_{C,K}$'s posterior distribution under each individual model weighted by the posterior probability of the model.

The prior model probabilities are often considered to be equal. The likelihood of a model is obtained by integrating over the model parameters. This yields a high-dimensional integral which may be difficult to solve analytically. There is a simple but accurate approximation which will be used in the scope of this thesis (cf. [Raftery et al. \(2005\)](#) for details). It uses the Bayesian information criterion (BIC) as follows:

$$2 \log p(D|M_n) \approx 2 \log p(D|\hat{\theta}_n) - \dim(\theta_n) \log |D| = -\text{BIC}_n \quad (3-5)$$

where θ_n are the parameters of the model M_n and $\hat{\theta}_n$ is the maximum likelihood estimator. $|D|$ refers to the sample size (i.e. number of surveys).

It is worth noting that there exist several techniques of general multi-model inference or model averaging that use information-theoretic methods to rank the models ([Burnham and Anderson, 2002](#)). Indeed, a non-negligible effect on the model-averaged response may arise from the selection of the information criterion (IC) that is used to assign a probability (or weight) to a model in terms of its relative quality to other models. Due to the limited number of travel surveys available, $|D|$ is small. A commonly used IC which is closely related to BIC is the Akaike information criterion (AIC) ([Akaike, 1973](#)) and its correction for small samples, AICc ([Sugiura, 1978](#)), which is used in this study. Its use is generally recommended over AIC ([Galipaud et al., 2014](#); [Burnham and Anderson, 2002](#)).

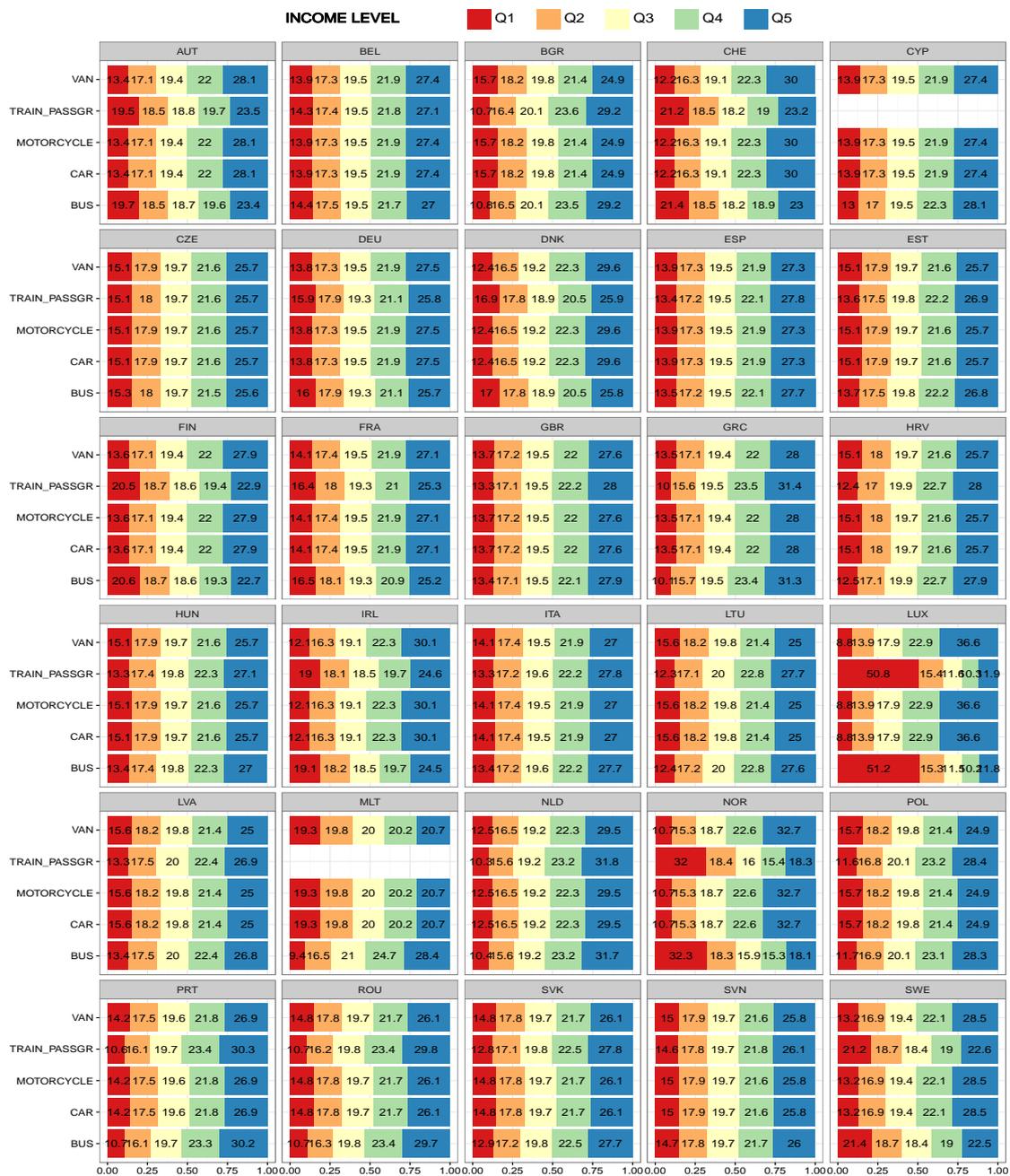


Figure 3-5: Share of PKM per income quintile (Q1 to Q5) per mode of transport and per country. The values were derived by the country- and mode-specific Lorenz curves described in the text. Note that there is no rail-bound traffic in Cyprus (CYP) and Malta (MLT).



Figure 3-6: Share of person-kilometres driven in a certain vehicle category per income quintile (Q1 to Q5) per country. Note that there is no rail-bound traffic in Cyprus (CYP) and Malta (MLT).

3.1.3 Distribution of vehicle stock and mileage over socio-economic groups

A motor vehicle is one of the major durable goods a consumer can own. General economics assumes that the average age of owned goods decreases with increasing income. This implies that vehicles owned by higher income groups tend to be replaced within shorter periods as opposed to lower income groups. Thus, understanding the distribution of vehicle ages in the population is important for policy-makers to understand socio-economic and environmental impacts of policies. The body of literature addressing this issue is rather limited but will be shortly presented in the following.

[Goodwin et al. \(2004\)](#) find an vehicle ownership elasticity with respect to real income of about -0.4 in the short-run and -1.0 in the long-run, so that a real income increase of 10% will raise ownership levels by about 4% and 10%, respectively. While this is a commonly found figure, the sole increase of vehicle ownership can only be used in a limited manner for an estimation of the age distribution of vehicles.

[Storchmann \(2004\)](#) generates depreciation data for a sample of 54 car models from 30 countries and investigates the correlation of depreciation and income. The author finds that the economic life of automobiles is, besides the prices for new cars, particularly dependent on real income. They find that an income increase by \$1,000 will likely increase annual depreciation rate by 2.7% in Organisation for Economic Co-operation and Development (OECD) countries in the long-run, and the same income increase will rise depreciation rate in non-OECD countries by 3.6%.

[Miller et al. \(2002\)](#) find that mean per capita income and median ages of passenger cars and light duty trucks are strongly negative correlated at -0.996 and -0.979, respectively, in a region-by-region analysis of Tennessee vehicle registration data. The authors find that median fleet age was highest in lowest-income regions and vehicles were newest in the highest-income county with median vehicle age at 10.8 years in the former and 5.9 years in the latter, resulting in significantly higher NO_x, carbon monoxide (CO) and volatile organic compound (VOCs) emissions in the former.

[Yurko \(2012\)](#) investigates how consumer income affects the distribution of age of vehicles utilizing Consumer Expenditure survey (CE) data published by the Bureau of Labor

Statistics at the US Department of Labor ([US Department of Labor, 2002](#)). At household level the author finds a negative correlation between income and age of vehicles owned, controlling for the size of vehicle stock possessed. Vehicle age distribution per category and country can be derived from the results of the TREMOVE model.

The overall aim is to find an assignment of PKM per income group I , vehicle category K and technology T . Furthermore, the assignment should follow the mode-specific Lorenz curves determined in chapter 3.1.2.

These requirements can be represented by a simple optimization problem as follows. The formulation is specified with the following two constraints.

The first constraint, g_1 , shall ensure that all mileage is distributed according to the given income group distribution. Thus, the constraint assures that for given category K all technology-specific VKM driven are distributed according to the shares of the respective income group following a distribution as determined in chapter 3.1.2.

The second constraint, g_2 , ensures that all mileage is distributed according to the given technology shares per category.

Recall that the solution shall maintain a certain vehicle age distribution across income groups. Therefore, ΔG_I is defined as the difference in average age of all vehicles of income group I compared to the income quintile below I , i.e. with lower income.

To maintain a distribution that meets the given constraints and deviates as little as possible from a given age distribution, the aim is to minimize the squared deviation for a given category K in country C . One can set

$$G_{I,C,K} = G_{C,K,T} \frac{\hat{a}_{I,C,K,T}}{L_{C,K}(\tau_{I,C}) \sum_T \hat{a}_{C,K,T}} \quad (3-6)$$

where

$G_{C,K,T}$ is the average vehicle age of vehicles in country C of category K and technology T ,

$G_{I,C,K}$ is the weighted average vehicle age of vehicle in country C of category K in income group I ,

$L_{C,K}$ is the estimated Lorenz curve of transport mode K in country C ,

$\tau_{I,C}$ is the cumulative share of total income for income group I ,

$\hat{a}_{I,C,K,T}$ is the reference level of activity conducted by income group I in country C within category K by technology T , and

$\hat{a}_{C,K,T}$ is the reference level of activity conducted by all income groups in country C within category K by technology T .

The aim is to minimize the squared deviation from the vehicle age distribution that is

$$\begin{aligned} \min \sum_I (G_{I+1,C,K} - (G_{I,C,K} + \Delta_{I,C,K}))^2 \\ \text{s.t.} \\ g_1 = \sum_T \hat{a}_{I,C,K,T} = L_{C,K}(\tau_I) \sum_T \hat{a}_{C,K,T} \\ g_2 = \sum_I \hat{a}_{I,C,K,T} = \hat{a}_{C,K,T} \end{aligned}$$

Thus, one needs to determine factors $\Delta_{I,C,K}$ and solve the non-linear optimization problem to estimate vehicle age distribution in a given country. However, $\Delta_{I,C,K}$ is difficult to estimate and is therefore deduced as described in the following. The model of [Yurko \(2012\)](#) predicts a strong negative correlation between vehicle age and income, so one can safely assume that $\Delta_{I,C,K} > 0, \forall I, C$ where K refers to individual travel.

Consider the average vehicle age of an income group relative to the mid-quintile average vehicle age. It can be observed from the data of the aforementioned study that this is inversely correlated with the average relative household income of that particular income group. This is not surprising as expenditures on mobility have always been important contributors to overall consumption and, as mentioned before, vehicle services are often considered the second most important durable consumer goods after expenditures on housing. In fact, the relative average vehicle age compared to the median age is about two third of the relative average income compared to the median income - so the effects is dampened which again highlights the importance of owning a vehicle (or having access to one). Unfortunately, due to the lack of more data on vehicle age distribution in other countries it is infeasible to further test the hypothesis, nor can uncertainty of the model itself be properly quantified.

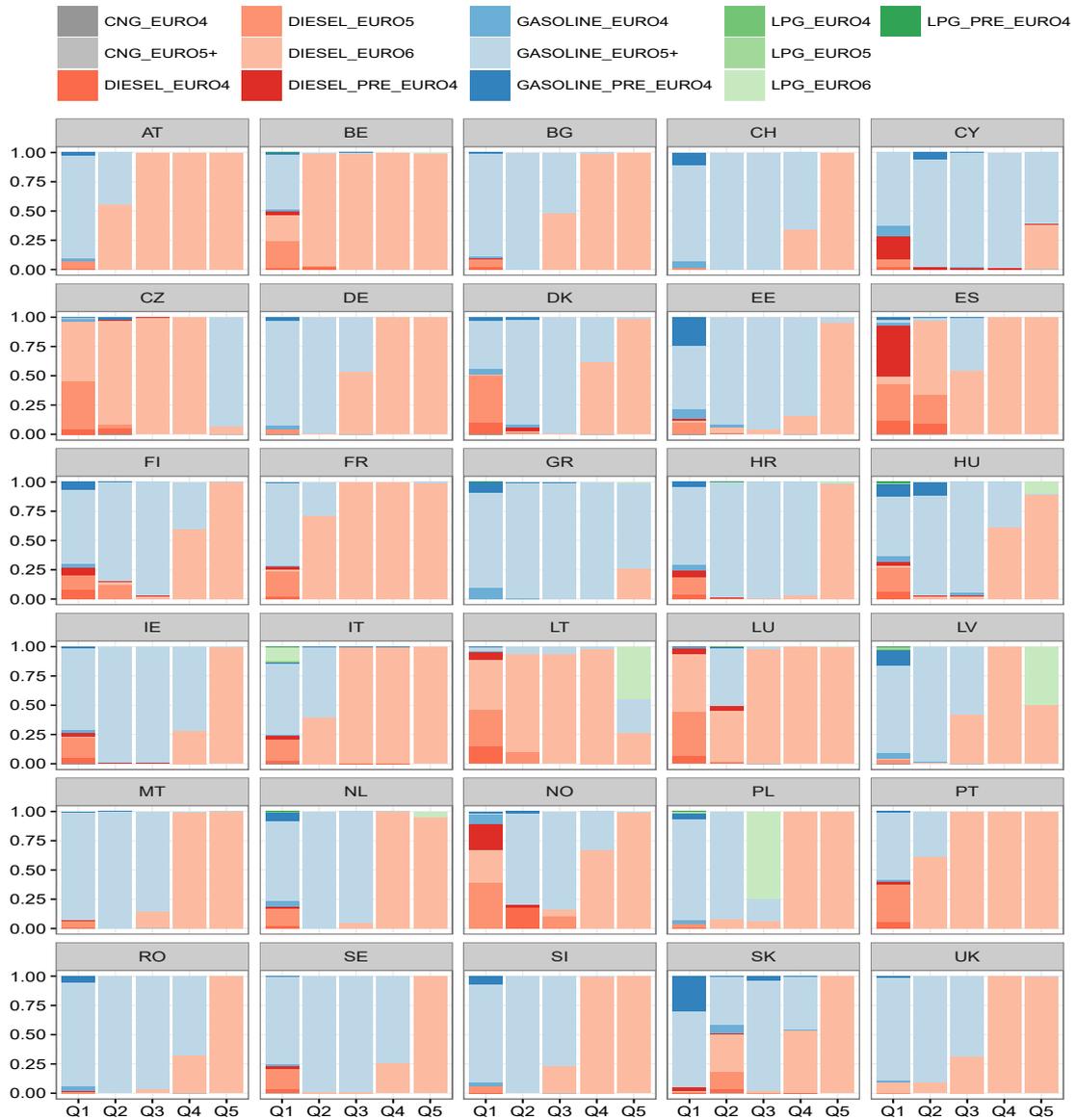


Figure 3-7: Share of fuel type and emission standard on the total person-kilometres driven by individual traffic (cars, vans and motorcycles) per income quintile (Q1 to Q5) and per country. There is a tendency of vehicle complying with 'older' emission standards (i.e. pre-Euro 4 and Euro 4) to be operated by lower income groups, and a tendency of 'newer' emission standards (i.e. Euro 5 and Euro 6) being present in mid-income and higher income groups.

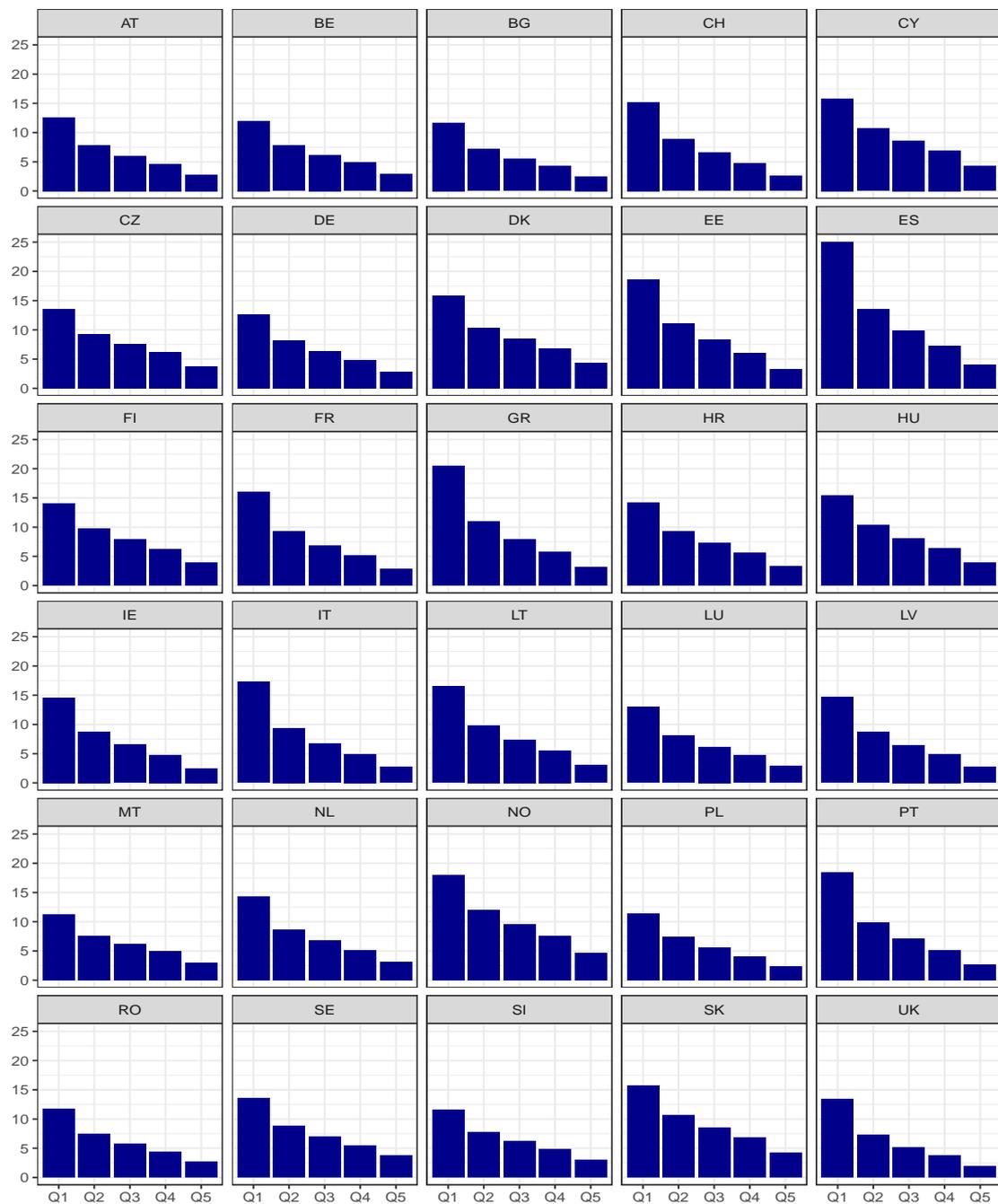


Figure 3-8: Average vehicle age (cars only) for income quintiles per country. A common pattern across countries is decreasing age with increasing income.

The distribution of vehicle category per income class in 2030 is shown in Figure 3-6. The distribution of emission standard compliance within the mode of non-public travel (i.e. cars, vans and motorcycles) is given in Figure 3-7. There is a tendency of vehicle complying with 'older' emission standards (i.e. pre-Euro 4 and Euro 4) to be operated by lower income groups, and a tendency of 'newer' emission standards (i.e. Euro 5 and Euro 6) being present in mid-income and higher income groups. Result for cars in 2030 are presented in Figure 3-8.

3.2 Data and uncertainty of emission factors

An emission factor (EF) is the amount emitted as a result of conducting a specific activity. The activity is given per task performed or sometimes per mass fuel burned. Consequently, it is defined as the emission rate of a given pollutant relative to units of activity. In the context of vehicle emissions the activity is given as distance travelled with the vehicle (VKM), the service provided by the vehicle in terms of passenger transport (PKM), or freight transported (ton-kilometre (TKM)). As indicated earlier, the EFs to a large extent depend on regional and temporal conditions as well as on vehicle characteristics. Specifically, they depend on vehicle category (e.g. cars, light-duty vehicles or trams) and fuel used (e.g. diesel, gasoline or liquefied petroleum gas (LPG)), but also road type, speed, meteorological conditions and after-treatment control devices fitted (Vouitsis et al., 2013a). Moreover, they depend on the emission standard fulfilled by the vehicle.

In the context of this thesis, EFs are given per PKM as the main unit of activity is PKM to allow for substitution of activities across different vehicle categories for instance passenger cars and trains.

3.2.1 On-road transport

Exhaust and non-exhaust emission factors for on-road transport are taken from the TRANSPHORM project (Vouitsis et al., 2013a,b). Many of the estimates were derived using the COPERT 4 methodology which covers a lot of the variation that exists due

to country-specific car fleet composition and speed limits, general driving conditions and climatic conditions. Due to the lack of tail pipe emission data, the estimates for vehicles classified as Euro 5 and beyond were derived by [Vouitsis et al. \(2013a\)](#) by relating results of a literature review to the COPERT data. The methodology is described in [EEA \(2012\)](#).

See Figure 3-9 and Figure 3-10 for diesel-fuelled and gasoline-fuelled cars, respectively. The values are given in mean grams emitted per PKM and are stratified by country, region (urban vs. non-urban) and period (peak vs. off-peak). The variation in emission factors across countries stems from different occupation rates and from a different fleet composition in terms of engine capacity. For instance, the original emission factors for passenger cars were grouped in three engine size classes, namely below 1.4 litres, between 1.4 and 2.0 litres, and more than 2.0 litres. The data was aggregated in this study to reduce the size of the optimization problem (cf. chapter 2). However, the country-specific distribution was maintained in a way that the emission factors were weighted by the share of an engine capacity class in the total PKM of the total fleet accordingly.

The Intergovernmental Panel on Climate Change (IPCC) published a guidance document which also deals with the identification and assessment of uncertainty of emissions in national greenhouse gas inventories ([IPCC, 2000](#)). Similarly, the EEA deals with uncertainty in their guidebook on air pollutant emissions inventories ([EEA, 2014c](#)). This information is used to determine the sectoral uncertainty of up- and downstream emissions of transport. The guidebook recommendations were used for the uncertainty analysis shown in Table 3-2. This table will be addressed in more detail later. However, the uncertainty ranges are rather rough and for the direct emissions of road-transport itself are considered not detailed enough. Therefore, different sources are used dedicating a more detailed analysis on this sector as described in the following.

A detailed analysis of uncertainty of road transport emission factors has been conducted by [Kouridis et al. \(2011\)](#). This is the main data source of uncertainty of road transport emission factors used in this thesis. The EEA also has dedicated recommendations for road transport uncertainties ([EEA, 2014b](#)) which also builds largely on [Kouridis et al. \(2011\)](#). The guidebook recommendations per vehicle category, technology and fuel type are listed in Table 3-3.

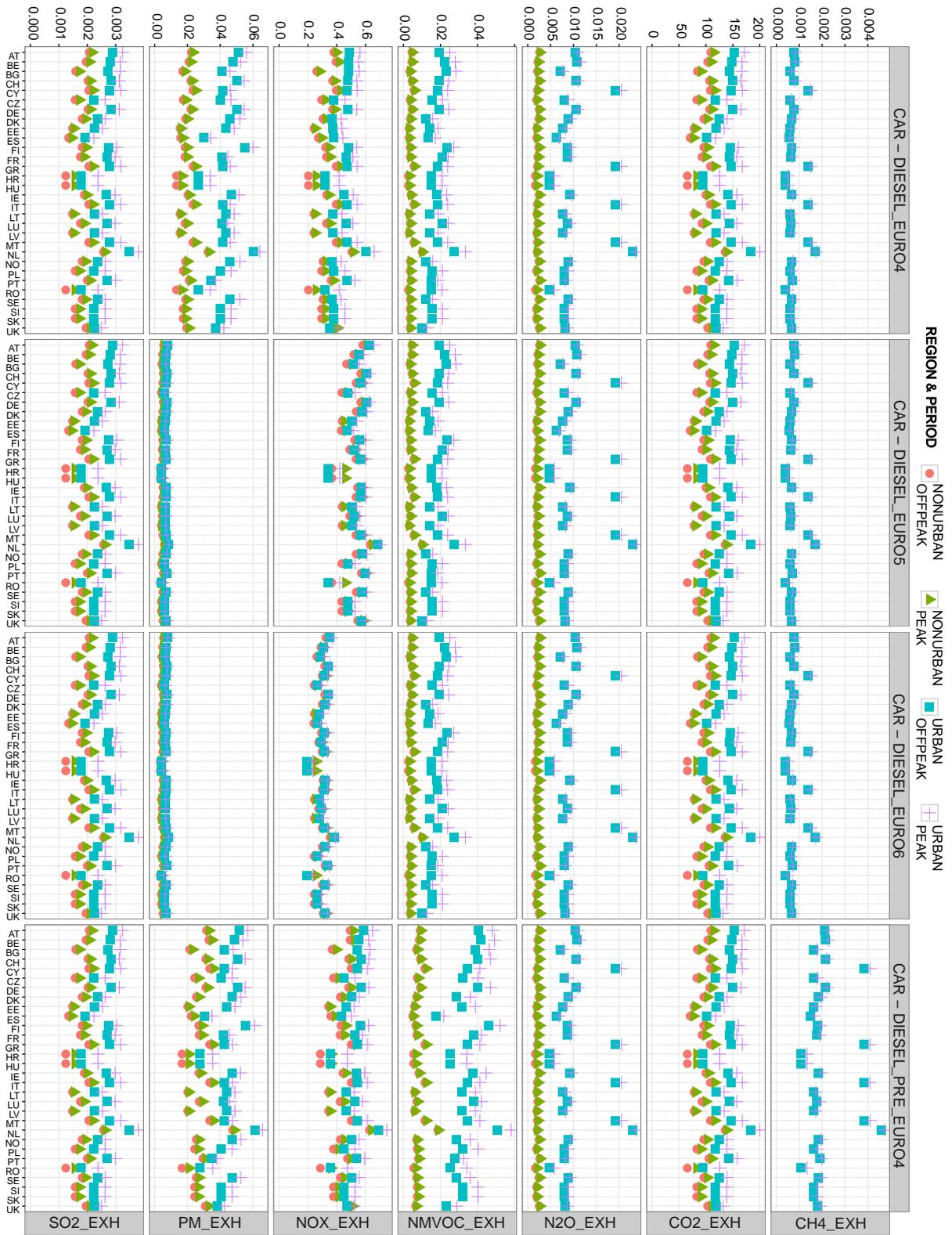


Figure 3-9: Mean reference emission factors [g/PKM] of diesel-fueled passenger cars stratified by fuel, emission standard and pollutant (uncertainties not shown).

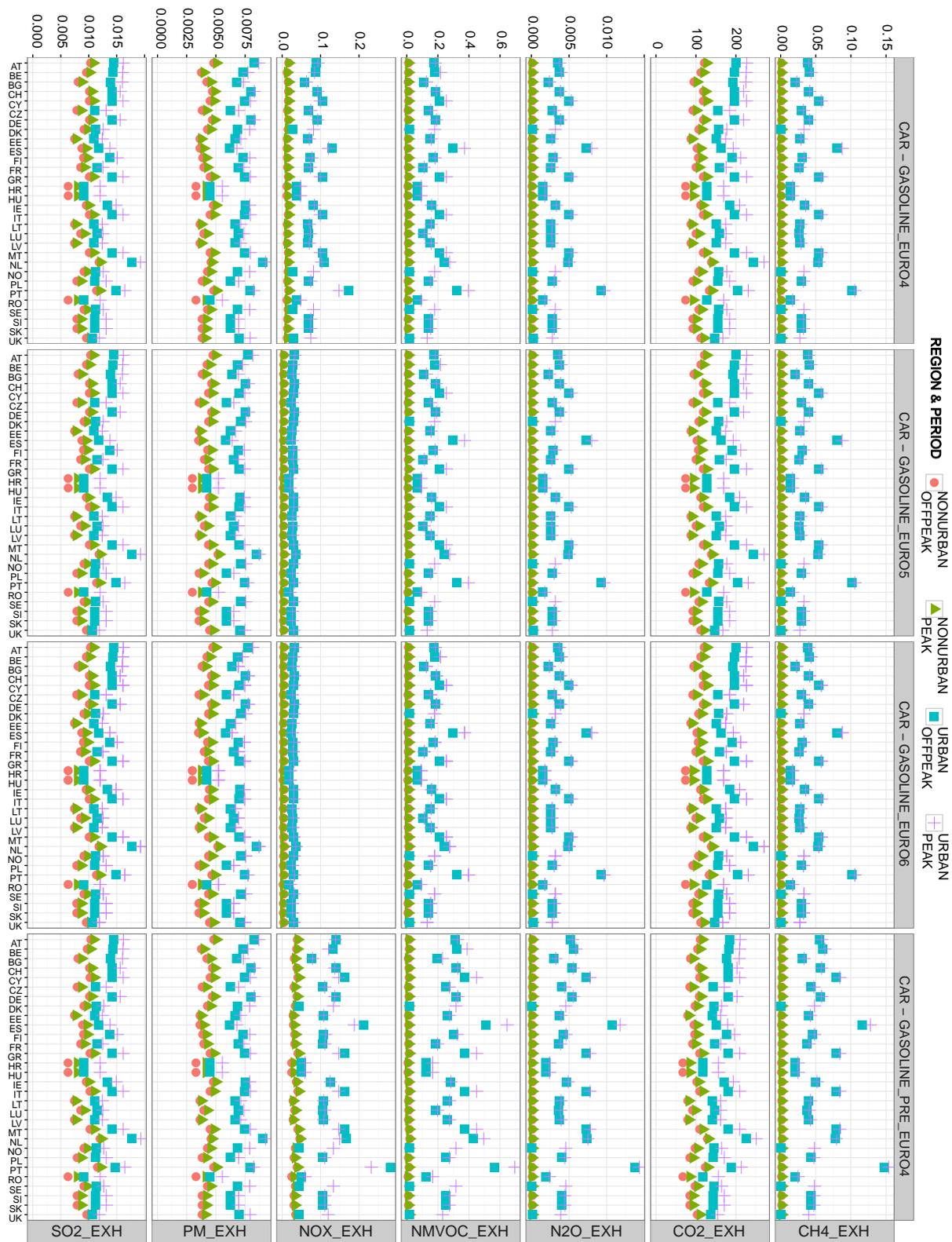


Figure 3-10: Mean reference emission factors [g/PKM] of gasoline-fueled passenger cars stratified by fuel, emission standard and pollutant (uncertainties not shown).

Note, that EFs for exhaust NO_x emissions of diesel-fuelled vehicles were adjusted in the scope of this thesis as irregularities between real driving emissions and measurements performed on a dynamometer were recently observed: Manufacturers and suppliers of the automotive industry have been accused of adjusting emission profiles of vehicles when under test. These adjustments result in substantially higher real-world NO_x emissions, especially from Euro 5 and Euro 6 diesel cars (Carslaw et al., 2011; Franco et al., 2014). The figures of an Umweltbundesamt (UBA) analysis are applied in the following which reports an average of 906 mg NO_x/VKM for Euro 5 diesel cars (limit: 180 mg NO_x/VKM), 674 mg NO_x/VKM for Euro 4 (limit: 250 mg NO_x/VKM) and 507 mg NO_x/VKM for current Euro 6 diesel cars without mandatory real driving emissions (RDE) test (limit: 80 mg NO_x/VKM) (UBA, 2017b). The values are transferred into g/PKM in Figure 3-9 with occupancy rates of about 1.5 PKM/VKM on average for passenger cars. However, even higher individual emission rates have been reported (cf. Carslaw et al. (2011); Franco et al. (2014)). Therefore, uncertainty of these estimates is assumed to be very high (see rating E for NO_x from diesel cars in Table 3-3).

There is also non-exhaust emissions from tyre and road surface wear. The emission factors vary across a variety of tires and road surface types (e.g. asphalt versus unpaved roads). Also, in some countries studded tyres are used. A significant contribution is also known to stem from re-suspension of road dust which also inhibits measurements, especially in tunnels, as re-suspended particles need to be distinguished from freshly abraded particles. Also, weather conditions are important to consider as the emissions vary if a road is dry or wet. Emission factors for road vehicle tyre and break wear and road surface wear are given in an EEA guidebook as well: The data used in EEA (2014d) were obtained using three different methods, namely by roadside receptor modelling at urban pollution hot-spots or in road tunnels, by airborne particle and wear factor determination in laboratory experiments and by applying a size distribution to wear factors in order to derive the airborne fraction. As a result, the authors estimate the uncertainty to be at ±50% as each of the methods is associated with significant uncertainty.

Additionally, there are evaporative emissions of non-methane volatile organic compound (NMVOC) from gasoline-fuelled vehicles. According to EEA (2014e) the contribution of evaporative NMVOC has been decreasing in recent years as a result of the introduction of

Table 3-2: Fuel-specific well-to-tank (WTT) resource production share of emissions along with quality data ratings for uncertainty assessment. Error ranges: A \triangleq 10 to 30%, B \triangleq 20 to 60%, C \triangleq 50 to 200%, D \triangleq 100 to 300%, and E is an order of magnitude.

Fuel type, life-cycle	CH ₄	CO ₂	N ₂ O	NMVOC	NO _x	SO ₂	PM
Diesel							
Crude oil production	80,7% (B ^f)	34,3% (A ^f)	50,8% (C ^f)	85,4% (C ^a)	54,8% (C ^a)	52,8% (C ^a)	57,8% (C ^e)
Crude oil distribution	3,1% (B ^f)	10,4% (A ^f)	15,1% (C ^f)	2,2% (C ^a)	14,7% (C ^a)	13,3% (C ^a)	4,1% (C ^e)
Low-sulphur diesel refining	14,3% (B ^f)	50,2% (A ^f)	25,2% (C ^f)	11,1% (C ^b)	23,5% (B ^b)	31,3% (A ^b)	33,0% (C ^e)
Low-sulphur diesel distribution & storage	1,9% (B ^f)	5,1% (A ^f)	8,9% (C ^f)	1,3% (C ^c)	7,0% (C ^c)	2,6% (C ^c)	5,1% (C ^e)
Gasoline							
Crude oil production	70,4% (B ^f)	23,4% (A ^f)	41,1% (C ^f)	77,7% (C ^a)	45,3% (C ^a)	38,6% (C ^a)	44,9% (C ^e)
Crude oil distribution	2,7% (B ^f)	7,1% (A ^f)	12,2% (C ^f)	2,0% (C ^a)	12,1% (C ^a)	9,7% (C ^a)	3,2% (C ^e)
Low-sulphur petrol refining	25,2% (B ^f)	65,9% (A ^f)	39,3% (C ^f)	19,1% (C ^b)	36,5% (B ^b)	49,7% (A ^b)	47,7% (C ^e)
Low-sulphur petrol distribution & storage	1,7% (B ^f)	3,6% (A ^f)	7,4% (C ^f)	1,2% (C ^c)	6,1% (C ^c)	2,0% (C ^c)	4,2% (C ^e)
CNG							
Natural gas production	24,8% (B ^f)	36,6% (A ^f)	26,5% (C ^f)	85,5% (C ^a)	30,2% (C ^a)	84,9% (C ^a)	69,5% (C ^e)
High pressure gas distribution & storage	75,2% (B ^f)	63,4% (A ^f)	73,5% (C ^f)	14,5% (C ^d)	69,8% (C ^d)	15,1% (C ^d)	30,5% (C ^e)
LPG							
Crude oil production	92,1% (B ^f)	49,6% (A ^f)	47,4% (C ^f)	92,1% (C ^a)	64,0% (C ^a)	33,8% (C ^a)	55,2% (C ^e)
Crude oil distribution	0,9% (B ^f)	7,5% (A ^f)	15,1% (C ^f)	0,8% (C ^a)	9,8% (C ^a)	25,8% (C ^a)	9,0% (C ^e)
Propane/butane refining	6,4% (B ^f)	38,5% (A ^f)	31,1% (C ^f)	6,1% (C ^b)	17,9% (B ^b)	38,5% (A ^b)	30,0% (C ^e)
Liquid petroleum gas distribution & storage	0,6% (B ^f)	4,4% (A ^f)	6,4% (C ^f)	1,0% (C ^c)	8,3% (C ^c)	1,9% (C ^c)	5,8% (C ^e)

^a NFR 1.B ^b NFR 1.A.1.b as part of 1.A.1 ^c NFR 1.A.3.b and 1.B, both apply

^d NFR 1.B.2.b as part of 1.B ^eecoinvent ^festimated from UK in [IPCC \(2000\)](#)

Table 3-3: Precision indicators of emission estimate for different vehicle categories (EEA, 2014b): A \triangleq statistically significant EFs based on sufficiently large set of measured/evaluated data; B \triangleq not significant, based on small set of data; C \triangleq estimated based on literature; D \triangleq estimated by similarity or extrapolation. E introduced to account for potential use of devices that may obfuscate real driving emissions of NO_x of diesel-fuelled vehicles under test conditions.

Vehicle category	NO _x	CO	NMVOC	CH ₄	PM	N ₂ O	NH ₃	CO ₂
Gasoline passenger cars								
without catalyst	A	A	A	A	-	C	C	A
with catalyst	A	A	A	A	-	A	A	A
Diesel passenger cars	A (E)	A	A	A	A	B	B	A
LPG passenger cars								
without catalyst	A	A	A	-	-	-	-	A
with catalyst	D	D	D	D	D	D	D	A
2-stroke passenger cars	B	B	B	D	-	D	D	B
Light commercial vehicles								
Gasoline	B	B	B	C	-	B	B	A
Diesel	B (E)	B	B	C	A	B	B	A
Heavy duty vehicles								
Gasoline	D	D	D	D	-	D	D	D
Diesel	A (E)	A	A	B	A	B	B	A
Two-wheel vehicles	A	A	A	B	-	B	B	A
Cold-start emissions								
Passenger cars								
Gasoline, conventional	B	B	B	-	-	-	-	B
Gasoline, Euro 1+	B	B	B	A	-	-	-	A
Diesel, conventional	C	C	C	-	C	-	-	B
Diesel, Euro I+	A (E)	A	A	A	A	-	-	A
LPG	C	C	C	-	-	-	-	B
Light commercial vehicles								
Gasoline	D	D	D	-	-	-	-	D
Diesel	D (E)	D	D	-	D	-	-	D

an activated carbon canister connected to the tank which adsorbs escaping fuel vapour. The emission factors are given in the EEA guidebook and rough uncertainty estimates by the means of precision indicators are recommended by [EEA \(2014e\)](#).

Table 3-2 shows the fuel-specific upstream (i.e. WTT) emission shares per key air pollutant and greenhouse gases from the life-cycle inventory database ecoinvent (see [Frischknecht et al. \(2005\)](#) for a description). The quality data ratings (in brackets) are collected and compiled from several sources of information:

- Data provided by the EEA per Nomenclature For Reporting (NFR) source category ([EEA, 2014c](#)); where Petroleum refining is NFR sector 1.A.1.b and NFR sector 1.B groups activities of extraction and distribution of fossil fuels (see table for details).
- Own estimates of error ranges derived from reported min-, mean- and max-values of emissions released per ecoinvent process.
- Greenhouse gas (GHG) emission uncertainties were estimated from the UK example given in the appendix 6A.2 of [IPCC \(2000\)](#).

The typical error ranges are as follows: A \triangleq 10 to 30%, B \triangleq 20 to 60%, C \triangleq 50 to 200%, D \triangleq 100 to 300%, and E represents an estimate based on an engineering calculation derived from assumptions only. The typical error of the latter is assumed to be an order of magnitude.

3.2.2 Rail-bound transport

In the previous section the data sources and uncertainty estimates for emission factors for on-road passenger transport were discussed. In the following values for rail-bound transport systems are presented. Nowadays, there are only two major power-train types of railway locomotives, namely electric and diesel. Steam locomotives have only very little contribution to emissions as they serve only very localised operations primarily as tourist attractions ([EEA, 2016](#)).

Diesel engines used in rail-bound transport are either fuelled by gas oil or conventional diesel fuel whereas the latter is similar to diesel used in on-road transportation, but the

former has higher sulphur content and higher density. The categorisation of [EEA \(2016\)](#) distinguishes three types of locomotives, as follows:

- Line-haul locomotives are equipped with diesel engines and are commonly used for long distance rail traction. Typical power output ranges from 400 to 4,000 kW.
- Rail-cars have about four times lower power output (about 150 to 1,000 kW) and are mainly used for short distance transport in urban or suburban areas. They are equipped with diesel engines as well.
- Shunting locomotives are equipped with diesel engines having power output typically in the range of 200 to 2,000 kW.

[Fridell \(2011\)](#) estimates specific fuel consumption (SFC) of 223 [206; 246] g/kWh. However, the power output ranges given by [EEA \(2016\)](#) are too broad to be used as an indicator of fuel consumption. [Fridell \(2011\)](#) also gives estimates of kg-fuel consumed per hour for the aforementioned categories, namely 53.9, 90.9, and 219 for rail-cars, shunting locomotives, and line-haul locomotives respectively. Emission factors for wear particles from railways are taken from [Fridell \(2012\)](#). To estimate emission factors for rail-bound transport the MJ per PKM are estimated based on figures from [Özdemir \(2012\)](#) assuming a consumption of 2 kg-fuel per 100 PKM. The figures are shown in Table 3-4.

Table 3-4: Specific fuel consumption of different categories of locomotives.

Category	Region	Fuel consumption [MJ/pkm]
Passenger train (Diesel)	Urban	900
Passenger train (Diesel)	Non-urban	800
Passenger train (Electric)	Urban	455
Passenger train (Electric)	Non-urban	234
Metro/Tram (Electric)	Urban	375

3.3 Uncertainty of air quality modelling

Despite advances in simulating chemical and physical processes the ability of air quality models to represent real-world conditions remains limited. As a result regional models still tend to under-estimate particulate matter mass concentrations when outcomes are compared to ground-based measurements (Pirovano et al., 2012; Denby et al., 2008). This becomes an issue in policy making when simulating the future effects of potential measures. As spatial representation remains inadequate due to computational limitations, the problem becomes especially evident when the aim is to improve air quality in urban areas (Torras Ortiz and Friedrich, 2013).

Evaluation of atmospheric models is difficult as modelled results can only be compared to past measurement data. These data are available from European air quality monitoring networks like EEA AirBase or EMEP – typically with a time lag of 2 or 3 years. However, for some pollutants measurements are scarce as focus has only recently shifted to them.

To determine the difference across models, modelled concentrations that are available from four state-of-science regional dispersion models (EMEP, LOTOS-EUROS, WRF-CMAQ and SILAM) as used in the TRANSPHORM project were analysed. Input data like meteorological fields and emissions data were agreed to be the same for all models¹. It has been shown that not all processes are well-understood as the estimated composition of particulate matter significantly differs across models even when driven by the same input data (Prank et al., 2014). Several approaches that aim to deal with these shortcomings exist: Models sometimes use data assimilation methods to have surface observation data support the estimation during the modelling process (see e.g. Vira and Sofiev (2015), Denby et al. (2008)). Others use statistical post-processing of model results to correct the bias of the models by comparing the model output to measurements (see e.g. Borrego et al. (2011), Manders et al. (2009), Delle Monache et al. (2008), Wilczak et al. (2006), McKeen et al. (2005)).

¹The methodology and underlying assumptions for the emission scenarios are described in Denier van der Gon (2011) and Denier van der Gon (2013)

3.3.1 Baseline and projected air quality levels

Obviously, the aforementioned strategies are only applicable for past years where proper measurements are available. Baseline $PM_{2.5}$ concentrations from these models are also available for 2005 but $PM_{2.5}$ measurements in this year are sparse. Interpolated maps for PM_{10} in 2005 exist along with a linear regression model based estimate of $PM_{2.5}$ but uncertainties reported are high.

Therefore, a model was developed in the scope of this thesis that estimates $PM_{2.5}$ from interpolated PM_{10} maps. EEA's 2005 air quality maps of PM_{10} are used as basis and estimate pseudo- $PM_{2.5}$ from EEA's AirBase PM_{10} measurements (Version 8 of the dataset). The 13 years period was selected for which measurement data are available (2000-2012). Data of 32 countries are considered, namely the EU28 member states, Norway, Switzerland, Ireland, and Iceland. Only considered data from background station below 700 m that measure $PM_{2.5}$ and PM_{10} and provide reasonable measurement quality (minimum coverage of 70% daily values per year for both pollutants; $1 \mu g m^{-3}$ cut-off value)².

The determined ratios (mean and standard deviation) are given in Table 3-5. Correlations coefficient to the stations longitude (r_{lon}) and latitude (r_{lat}) coordinate and the year of the measurement (r_{year}) are shown. Obviously, the type of station has almost no effect on the mean $PM_{2.5}$ -to- PM_{10} ratio. The annual average ratio follows a right-skewed distribution with considerable variance.

However, the variance can be explained partly by correlation to the station coordinates but seems to undergo temporal variation to a much lesser extent. The latter encourages use of a prediction model in other years than the period used to train a model (e.g. when conducting leave-one-out cross-validation by removing the year 2005 from the 13 years period).

It was previously observed that the distinction made in AirBase into urban, suburban and rural is inconsistent (see e.g. [Beelen et al. \(2009\)](#)). There exists a more detailed distinction of suburban and rural stations into whether they are near cities or whether they are remote, however, this information is not given for the majority of stations. Thus, all station data available was collected and stations were reclassified subsequently

²Similar assumptions as e.g. in [Pirovano et al. \(2012\)](#)

Table 3-5: Annual average PM_{2.5}-to-PM₁₀ ratio follows a right-skewed distribution with considerable variance. However, the variance can be explained partly by correlation to the station coordinates but seems to undergo temporal variation to a much lesser extent. This encourages use of a prediction model in other years than the period used to train a model (e.g. when conducting cross-validation by removing the year 2005 from the 13 years period).

Type of stations	obs.	μ (σ) of PM _{2.5} -PM ₁₀ ratio	r_{lon}	r_{lat}	r_{year}
urban	1246	0.65 (0.18)	0.34	0.30	0.12
suburban	330	0.64 (0.13)	0.59	0.58	-0.11
rural	388	0.62 (0.12)	0.42	0.23	0.05

by incorporating information of the population density in the area where the station is located (see Table 3-6). The spatial correlation can be used and a prediction model can be developed that estimates PM_{2.5} from PM₁₀ along with other variables that take into account geographical or surface conditions of the area and meteorological conditions.

A random forest model is developed as a non-linear estimator which uses cross-validation within the training process by design. The model is assessed by leaving out data from the year 2005 for validation and using the period 2000-2004 along with 2006-2012 for training. The data used are shown in Table 3-6. Relative importance of the variables is given in Figure 3-11. The right figure shows the importance of individual variables in decreasing order. The value represents the theoretical increase in error if the individual variables were left out. The model is able to explain 92% of the variance within the training data ($N = 2014$ observations in 2000-2004 and 2006-2012). When applied to the test data ($N = 98$ observations in 2005) the value of R^2 is at a remarkable 0.87.

3.3.2 Intra-model uncertainty of atmospheric models

Systematic underestimation of particulate matter concentrations, sometimes referred to as 'PM deficit', has been frequently reported in chemical transport modelling studies (cf. [Prank et al. \(2016\)](#)). Usually, an atmospheric model runs under deterministic conditions

Table 3-6: Datasets used to develop random forest model. Temporal coverage and spatial resolution refer to the data used to feed into the model. The population density was aggregated to 1 km² to cover a more representative area.

Dataset	Variables	Temporal coverage	Spatial resolution
ETC/ACC interpolated air quality maps ^a	PM ₁₀	2005	10 × 10 km ²
EEA AirBase v8 ^b	PM _{2.5} , PM ₁₀	2000-2012	at station
ECMWF ERA-Interim ^c	2m temperature, 10m wind speed, 10m U wind comp., 10m V wind comp., Surface roughness, Air pressure, Cloud cover, Relative humidity, Boundary layer height	2000-2012	1/8° × 1/8°
GLCF/MODIS ^d	Land cover type	2001-2012	1/12° × 1/12°
JRC Population Grid ^e	Population density	2001	1 × 1 km ²

^a ETC/ACC (2008) ^b EEA (2014a) ^c ECMWF (2015) ^d Channan et al. (2014)
^e Gallego (2010)

where no uncertainty in the input parameters nor in the model formulation is assumed. Obviously, this is a simplification of reality, reducing complexity to a great extent. A further trade-off in simplicity and computational tractability is achieved by limiting the number of chemical reactions performed, representing states of the environment on a rather coarse grid, and using aggregated, uncertain input – just to mention a few – yielding some processes and interactions being likely to be under-represented or not captured at all. Obviously this is necessary for being able to represent the problem as a formal process and to limit running time of the model, but the outcome is clearly biased (cf. Kukkonen et al. (2012)).

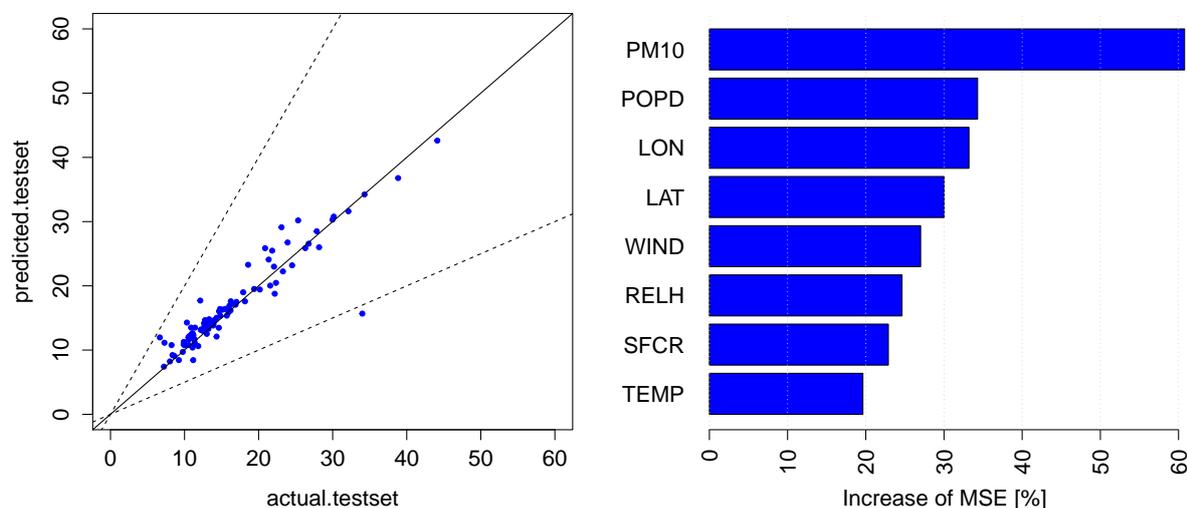


Figure 3-11: Scatter-plot of observed and predicted $\text{PM}_{2.5}$ annual average in 2005 ($R^2 = 0.87$, $N = 98$). Observations were made at ground-based stations. Predictions were made by a random-forest model. Input variables are ranked by importance given as the increase of mean-square error (MSE) occurring when removing one of the variables individually (PM_{10} = Observed PM_{10} level; POPD = Population density; LON = Longitude; LAT = Latitude; WIND = Wind speed at 10m; RELH = Relative humidity; SFCR = Surface roughness; TEMP = Temperature at 2m).

With the aim of overcoming these limitations model ensemble studies utilizing multiple atmospheric models are conducted (e.g. Prank et al. (2014)). One can observe from an example shown in Figure 3-12, how projected reduction of fine particles in 2030 (relative to 2005) differ across models: Mean reduction and standard deviation are shown across the aforementioned four state-of-science regional dispersion models (EMEP, LOTOS-EUROS, WRF-CMAQ and SILAM). Even though the models are forced by the same data in terms of emissions and meteorology, there is considerable disagreement with respect to model outcome. This will be referred to as the model-intrinsic uncertainty.

However, using a parametrized model may even amplify this effect (see chapter 3.3.3). Baseline concentration levels are important in subsequent damage estimation. Thus, it is necessary to deal with the uncertainties arising from the modelling limitations stated above as is done in the following. To properly distinguish uncertainties along the IPA,

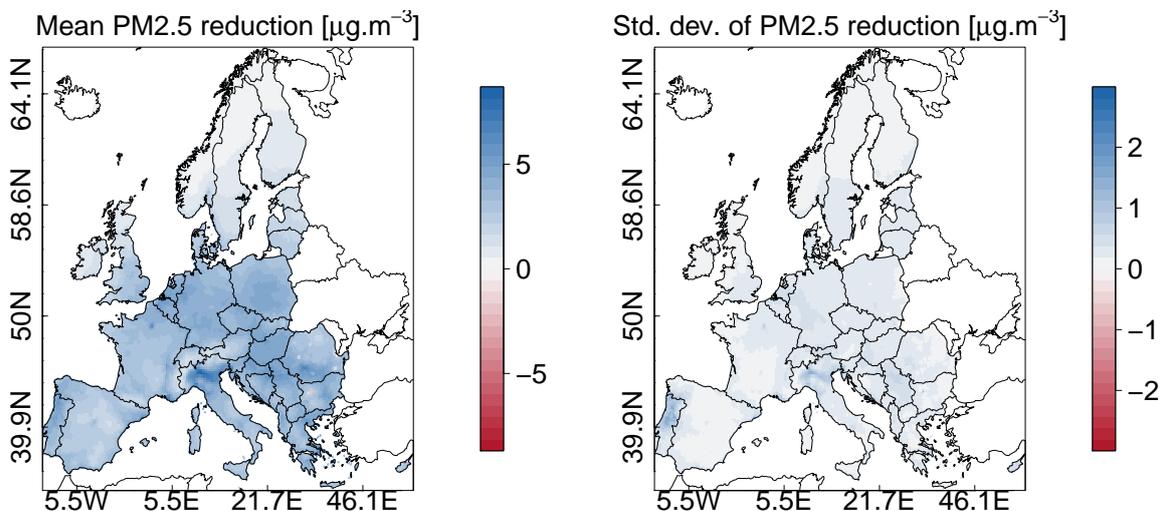


Figure 3-12: Estimated projected reduction of baseline PM_{2.5} levels until 2030. The reduction was estimated using results of a model ensemble as described in this document. Mean (left) and standard deviation (right) are given whereas the deviation stems is due to different model formulations only (driven by same data).

the source of uncertainty needs to be addressed that is not related to uncertainties in the emissions but originates from the atmospheric model implementation. The uncertainty partly exists due to incomplete understanding of physical and chemical processes yielding mistaken model formulation.

Determining the predominant source of uncertainty is rather difficult because separating the sources in the first place is hard: As an example, [Zhou et al. \(2013\)](#); [Gilliland et al. \(2008\)](#) found that air quality models may underestimate ozone concentrations by up to 60% when comparing the results to observations. Albeit ozone modelling has been studied for decades, the source of error is not necessarily evident. Whereas the main source of uncertainty has been identified to be estimated ground nitrogen oxide emissions according to [Zhou et al. \(2013\)](#), [Gilliland et al. \(2008\)](#) showed that the error can also be attributed to inefficient modelling of long-range transport of ozone and precursors, as well as inaccurate representation of meteorological variations or the chemical mechanism chosen.

On the other hand, parameter setting like, for instance, the size of a grid cell greatly influences the results of the model and may lead to suboptimal results not only for

concentrations modelling but also for the subsequent health impact assessment (Denby et al., 2011). Grid size is a crucial factor and represents the necessary trade-off between run-time of the model and level of detail of the output.

Furthermore, random processes from meteorological conditions yield inherent uncertainty. They are discussed in chapter 3.3.3. Obviously, further input like land-use data is as well subject to uncertainty. For the sake of tractability of the results the uncertainty of the aforementioned effects are estimated in an aggregated manner.

The results of four atmospheric models are compared for $PM_{2.5}$ and three models for NO_2 with the respective measurements in the study period based on EEA's AirBase measurement data. While a lot of measurements exist for NO_2 , data for $PM_{2.5}$ is fairly limited. A methodology is presented to overcome sparse $PM_{2.5}$ measurement data in chapter 3.3.1. However, in this context it is not intended to introduce any extra uncertainty and thus the measurement data is relied on.

Results for NO_2 data for $PM_{2.5}$ stratified into urban and non-urban regions are given in Figures 3-13 to 3-16. For $PM_{2.5}$, it is evident that all models suffer from the aforementioned deficit of properly estimating levels of fine particulates. The mean relative deficit ranges from a factor of 1.18-1.95 in non-urban areas with a considerable geometric standard deviation (GSD) of 1.36 to 1.58 in rural areas. The mean relative PM deficit is even higher in urban areas at 1.41-1.94 at a similar GSD of 1.40 to 1.53.

Levels of NO_2 in rural areas are on average properly modelled though with considerable GSD of 1.62 to 1.85. However, in urban areas the models suffer from a high deficit underestimating the measured data on average by 2.25-2.37 whereas GSD is about the same as for rural areas.

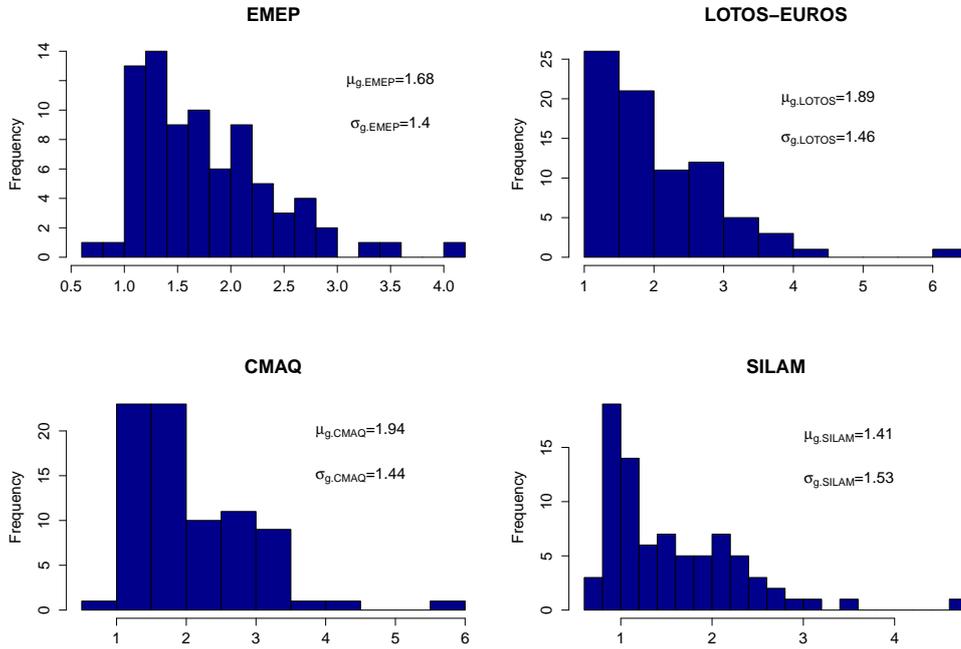


Figure 3-13: μ_g (geometric mean) and σ_g (GSD) of four modelled urban $PM_{2.5}$ levels compared to AirBase measurements in 2005.

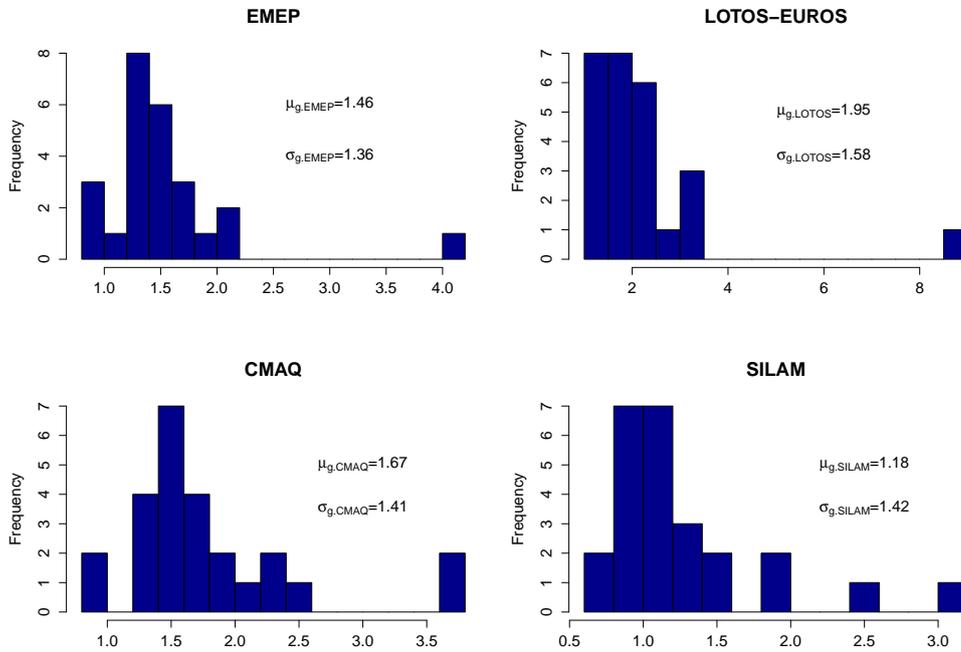


Figure 3-14: μ_g (geometric mean) and σ_g (GSD) of four modelled rural $PM_{2.5}$ levels compared to AirBase measurements in 2005.

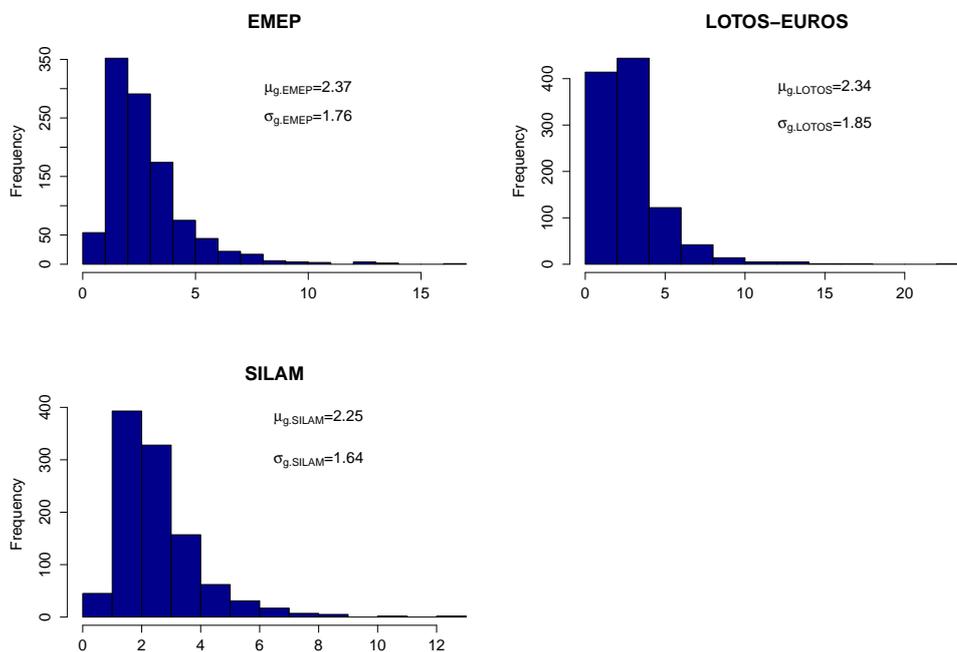


Figure 3-15: μ_g (geometric mean) and σ_g (GSD) of four modelled urban NO₂ levels compared to AirBase measurements in 2005.

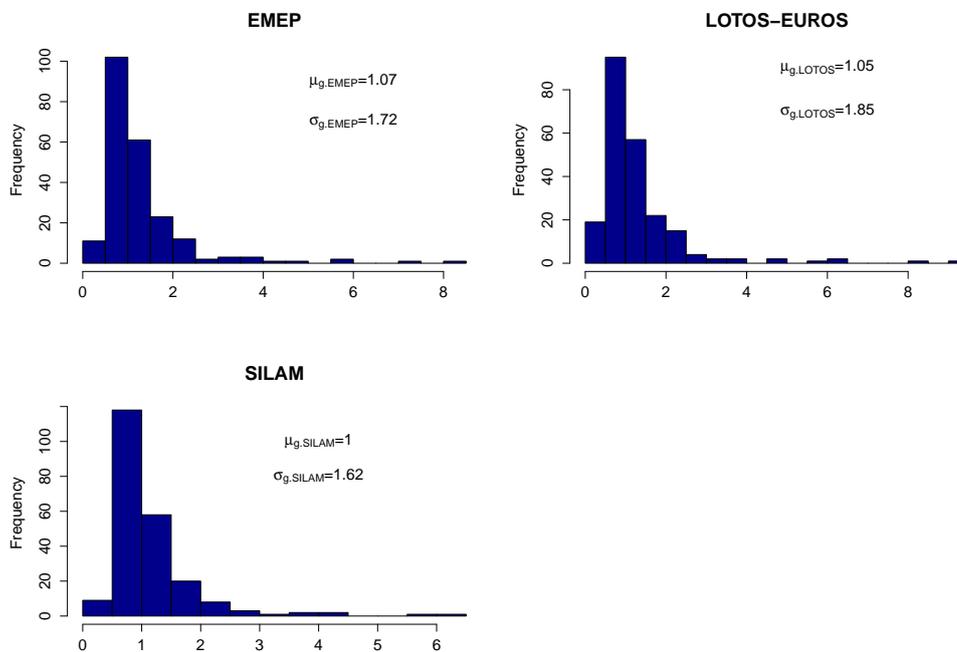


Figure 3-16: μ_g (geometric mean) and σ_g (GSD) of four modelled rural NO₂ levels compared to AirBase measurements in 2005.

3.3.3 Parametrized modelling of air quality gradients

Recall from eq. (2-16) and eq. (2-20) (chapter 2) that it is assumed that a concentration change of some pollutant at a receptor is both additive in the amount of precursor emissions and in the contributing sources. Furthermore, it is assumed that it is linear in the amount of emission released per precursor with respect to a certain interval of emissions change (see chapter 2.2.3). It should be acknowledged that, in reality, these processes are non-linear. In fact, there are several approaches that aim to preserve some of the non-linearity of the full-scale atmospheric model when generating surrogate models (e.g. [Carnevale et al. \(2009, 2012a\)](#)).

However, others investigated the validity of assuming linearity under certain circumstances: [Bultjes et al. \(2012\)](#) investigate the linear relationship between NH_3 emission reduction and PM_{10} concentration change. The authors find that it is valid to assume linearity for up to 10% change in emission of the contributing precursor. However, they conclude that this assumption becomes highly unreasonable for reductions beyond 25%. [Wind et al. \(2004\)](#) perform several sensitivity analyses to determine the adequacy of the approximation stated compared to a full EMEP model run with respect to PM precursors and ozone formation. The authors conclude that the approximation is correct for small changes in emission relative to the scenario used to determine the source-receptor relationship. However, they also state that the approach might fail when moving too far away from this scenario because of higher order derivatives in the exact equation of the full model.

The EMEP model is described in [Simpson et al. \(2012\)](#). [Tarrason et al. \(2003\)](#) estimate the non-linear effects in the EMEP model regarding SIA surface concentrations to be in the low single-digit range. [Wind et al. \(2004\)](#) suggest based on their findings that, with respect to interpolation between the base scenario and a 15% reduction of precursor emissions, non-linear effects can be neglected. Differences were shown to be below 5% for all considered precursor-emission/pollutant-concentration ratios of the parametrized model and the full model when reducing single precursors in the 25 EU countries, at that time, simultaneously. Even regarding a 50% reduction, representing a strong extrapolation, [Wind et al. \(2004\)](#) show that SO_4^{2-} concentrations were mostly within 5% of the modelled results. Concentration of aNO_3 and NH_4^+ showed higher deviations but of

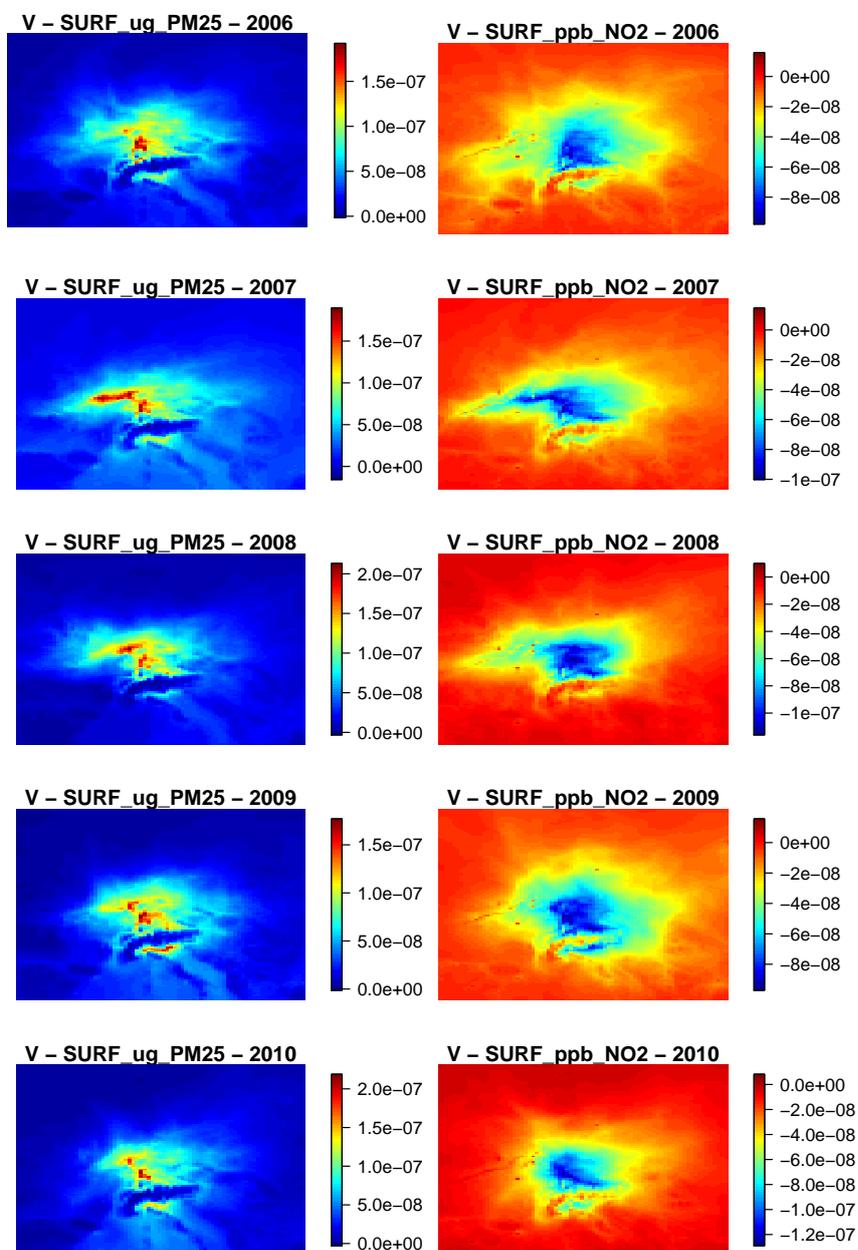


Figure 3-17: Source-receptor matrices for Germany based due to one ton reduction of VOC (V) and changes at surface level (<2m). The figures show change of PM_{2.5} [$\mu\text{g}/\text{m}^3$] on the left and change of NO₂ [ppb/m^3] on the right. The difference is shown relative to a base year but with varying meteorological conditions of five years from 2006 to 2010.

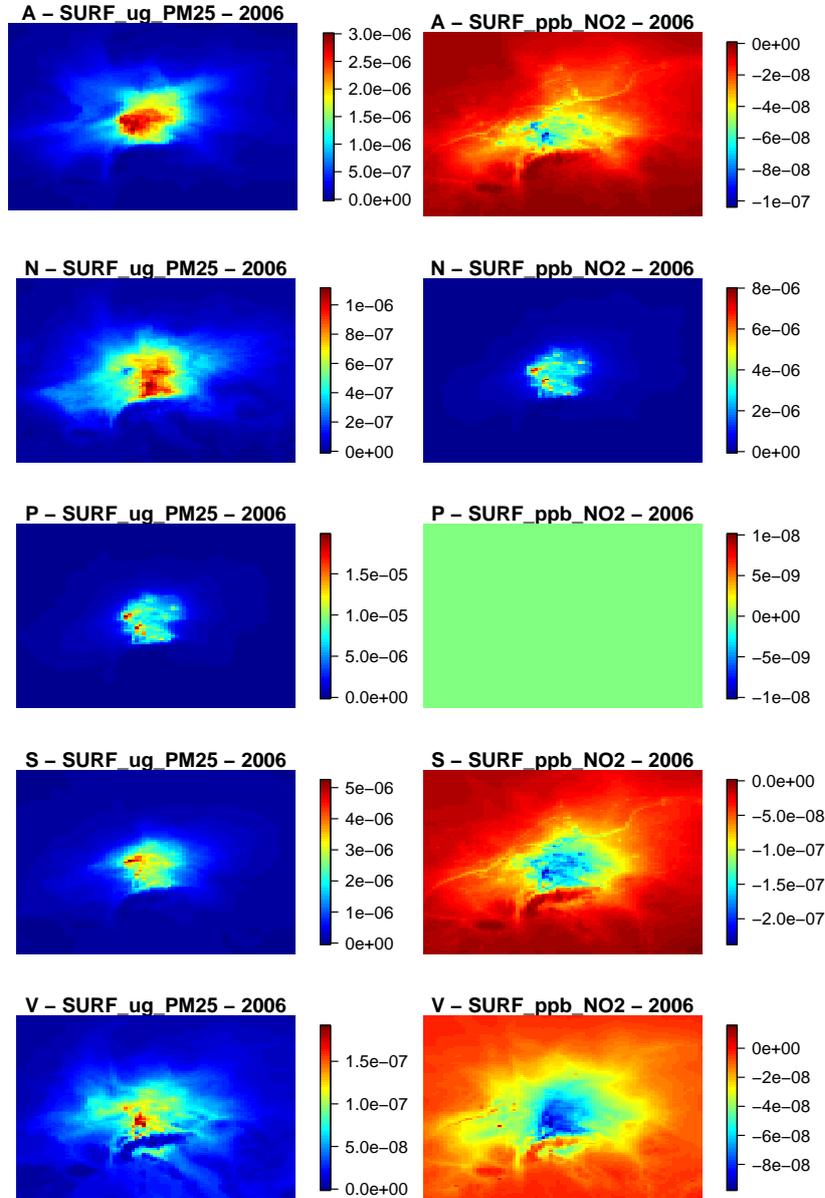


Figure 3-18: Source-receptor matrices for Germany based on 2006 meteorology and changes at surface level (<2m). The figures show change of PM2.5 [$\mu\text{g}/\text{m}^3$] on the left and change of NO₂ [ppb/ m^3] on the right. The changes are due to one ton emissions change of one of the following five precursors respectively: Ammonia (A), nitrogen oxides as NO₂ (N), primary fine particles <2.5 μm aerodynamic diameter (P), sulphur oxides as SO₂ (S) and VOC (V).

acceptable 10-20%, mostly in Southern Europe. AOT40 deviations seem to be harder to characterize showing also variations of the range of 10-20% for most of the receptor cells, but some higher deviations over maritime regions like the North Sea including coastal areas of neighbouring countries.

The source-receptor matrices utilized in this thesis are based on EMEP model runs prepared for the Thematic Strategy on Air Pollution (TSAP) in 2012 and provided in the scope of the TRANSPHORM project. The matrices give indication of changes of concentration at receptor sites (here at a grid resolution of 0.5×0.25 degree over Europe). The model runs were forced by emissions from the TSAP 2012 scenarios and a reduction of individual precursor emissions in individual countries. Note that no distinction between emissions release height was made as was the case in earlier use of the model in the NEEDS project (Tarrason, 2009). However, meteorological conditions were varied across years 2006 to 2010 by separately rerunning the reduction scenarios. As an example, the effect of meteorological conditions on the same reduction scenarios in Germany is shown in Figure 3-17 for Germany for both NO_2 and $\text{PM}_{2.5}$. Also, the different effects of the precursor reductions on the concentration change of both NO_2 and $\text{PM}_{2.5}$ are shown when precursors were reduced separately. The following five precursors were considered (see Figure 3-18): Ammonia (A), nitrogen oxides as NO_2 (N), primary fine particles $<2.5\mu\text{m}$ aerodynamic diameter (P), sulphur oxides as SO_2 (S), and VOC (V).

3.4 Data and uncertainty of exposure-response modelling

3.4.1 Exposure-response relationships

The World Health Organization (WHO) established guidelines on improving air quality in 2005. The European Parliament directive 2008/50/EC states that emissions of harmful air pollutants should be avoided, prevented or reduced. Also, the directive demands that appropriate objectives should be set for ambient air quality. In a recent extensive review (co-financed by the WHO and the European Commission (EC)), health aspects of air

pollution that are of relevance for the review of European Union policies were investigated within the REVIHAAP project (WHO, 2013b). As considerable amount of new scientific evidence on health effects of particulate matter, ozone and nitrogen oxides emerged, several concentration-response functions (CRFs) were identified and recommended for the use of cost-benefit analysis (CBA) of EU policies in the scope of the HRAPIE project (WHO, 2013a).

Regarding the implementation of the HRAPIE recommendations in the context of a CBA, WHO (2013a) classifies the pollutant-outcome pairs in two categories as follows:

- Group A: pollutant-outcome pairs for which enough data are available to enable reliable quantification of effects;
- Group B: pollutant-outcome pairs for which there is more uncertainty about the precision of the data used for quantification of effects.

The authors give the effect estimates for pollutant-outcome pairs marked with an asterisk (*) when they contribute to the total effect in an additive manner. The confidence intervals (CIs) of the CRFs cover the uncertainty in the risk estimate as they represent the random error and the variability in the effect estimate across the epidemiological studies investigated. Calculation of the range of overall costs and benefits is recommended to be based on the following principles whereas uncertainty estimates should additionally be made using Monte Carlo estimates based on the CI of the respective relative risk (RR):

- The limited set of impacts is given by summing over the effects of group A*. The uncertainty ranges are then given by the sum over the minimum of A* or A as the lower bound and by the sum over the maximum of A* or A as the upper bound.
- The extended set of impacts is given by summing over the effects of both A* and B*. The lower bound of the uncertainty range is then given by the sum over the minimum of A* or A plus the minimum of B* or B. Analogously, the upper bound of the uncertainty range is given by the sum over the maximum of A* or A plus the maximum of B* or B.

To determine the loss of life expectancy (LLE) (or its gain) due to changing levels of air pollution one accounts for the decrease of risk after the exposure to a certain level of

Table 3-7: RR and CRFs for long-term exposure to PM, O₃ and NO₂ as recommended by (WHO, 2013a).

Pollutant metric ^a	Health outcome	Group	RR (95% CI) per 10 µg/m ³	Range of concentration
PM _{2.5}	Mortality, all-cause, adults 30+ years	A*	1.062 (1.040-1.083) ^c	All
PM _{2.5}	Mortality, cerebrovascular disease (incl. stroke), ischaemic heart disease, chronic obstructive pulmonary disease and trachea, bronchus and lung cancer, adults 30+years	A	CVD: 1.07 (1.02-1.14) ^d ; IHD: 1.14 (1.07-1.21) ^d ; COPD: 1.05 (1.01-1.10) ^d ; LC: 1.06 (1.01-1.12) ^d ;	determined ^b at 12 µg/m ³
PM _{2.5}	Mortality, acute lower respiratory illness, children < 5 years	A	ALRI: 1.04 (1.01-1.09) ^d	determined ^b at 12 µg/m ³
PM ₁₀	Infant mortality, all-cause, children ≤ 1 year	B*	1.04 (1.02-1.07) ^e	All
PM ₁₀	Prevalence of bronchitis, children 6-12 or 6-18 years	B*	1.08 (0.98-1.19) ^f	All
PM ₁₀	Incidence of chronic bronchitis, adults 18+ years	B*	1.117 (1.040-1.189) ^g	All
O ₃ , in summer, avg. of daily max 8-hr mean >35 ppb	Mortality, respiratory diseases, adults 30+ years	B	1.014 (1.005-1.024) ^h	>35 ppb (>70 µg/m ³)
NO ₂	Mortality, all-cause, adults 30+ years	B*	1.055 (1.031-1.080) ⁱ	>20 µg/m ³

^a Annual mean metric of the original report.

^b Own calculation: All-age estimate of the Integrated Exposure-Response model determined at estimated future background of 12 µg/m³ (population weighted PM_{2.5} in Europe ranges from 11 to 17 µg/m³ in 2005 (Brauer et al., 2012)). ^c Hoek et al. (2013) ^d IHME (2013)

^e Woodruff et al. (1997) ^f Hoek et al. (2012) ^g AHSMOG and SAPALDIA studies

^h Jerrett et al. (2009) ⁱ Up to 33% overlap with PM_{2.5} effects of group A.

Table 3-8: All-cause background mortality per 100,000 people (Age-standardized death rate (SDR) calculated by WHO using standard European population structure.).

Country	2008	2009	2010	2011	2012	2013	2014
Austria	558.02	564.24	549.10	532.24	538.13	529.06	511.26
Belgium	591.15	577.29	576.66	559.48	568.01		
Bulgaria	995.39	964.65	970.26	932.87			
Croatia	829.79	813.07	789.62	761.25	754.15	721.47	
Cyprus	536.03	515.40	489.39	509.61	514.84		
Czech Republic	746.21	743.94	724.19	708.43	700.65	691.86	
Denmark	652.17	644.37	628.53	597.29	583.14		
Estonia	893.13	839.50	799.67	759.72			
Finland	586.78	579.94	573.77	554.36	551.01	535.12	
France	517.07	508.83	500.62	484.55			
Germany	582.46	575.92	565.56	549.44	545.34	563.89	
Greece	595.53	577.20	557.98	547.86	553.13		
Hungary	926.23	914.91	898.57	875.36	871.48	840.71	
Ireland	593.61	591.06	553.96	550.8	548.35		
Italy	502.91	495.59	478.12	481.92	483.17		
Latvia	1,033.65	982.40	973.58	915.05	910.88		
Lithuania	1,027.80	957.86	945.79	911.04	893.10		
Luxembourg	528.77	527.77	524.44	519.96	495.92	476.60	
Malta	597.03	570.62	516.61	538.6	544.53	496.35	487.16
Netherlands	566.19	549.18	543.16	528.18	533.51	522.53	
Norway	549.20	536.95	531.18	521.19	518.59	505.91	
Poland	819.26	809.66	771.49	747.68	746.83	734.31	
Portugal	613.06	600.28	586.10	555.64	562.31	546.91	
Romania	964.34	959.48	948.01	901.32	901.31		
Slovakia	882.95	860.31	849.66				
Slovenia	631.92	625.13	599.67				
Spain	519.73	503.66	487.01	481.45	477.08	452.91	
Sweden	533.12	520.27	514.07	503.71	507.73	496.56	
Switzerland	477.80	475.64	464.08	455.76	457.69	452.85	
United Kingdom	590.91	562.64	553.08	533.63			
EU28	622.48	609.41	595.02	579.06	577.68		

pollution decreases. To determine and assess the full effects of air pollution on health it is important to go beyond the short-term (i.e. more or less acute) effects that can be measured by time series epidemiology. However, long-term studies (i.e. those measuring chronic effects) are very costly and, thus, not many of them exist. Table 3-7 summarizes the recommendations of WHO in terms of RR as a factor of age-specific relative risk of chronic mortality (as opposed to acute mortality).

The analysis of the chronic effects is usually done using dynamic models, implicating the utilization of age distribution and mortality data of a population. [Leksell and Rabl \(2001\)](#) define age specific mortality rate $\mu(x')$ such that someone who has reached age x' has a probability $\mu(x')\Delta x'$ of dying between age x' and $x' + \Delta x'$. One can then define $S(x, x')$ as the fraction of a cohort of age x that survives until age x' or beyond. $S(x, x')$ is called the survival function. The fraction of the cohort that dies between x' and $x' + \Delta x'$ is the change in the survival function $\Delta S(x, x')$ being equal to $S(x, x')\mu(x')\Delta x'$, so the differential equation is as in [Leksell and Rabl \(2001\)](#):

$$dS(x, x') = -S(x, x')\mu(x') dx \quad (3-7)$$

Obviously, $S(x, x) = 1$, and for $x' > x$ [Leksell and Rabl \(2001\)](#) find that

$$S(x, x') = \exp\left(-\int_x^{x'} \mu(x'') dx''\right) \quad (3-8)$$

$S(x, x')\mu(x')$ is the probability distribution for someone of the cohort of age x to survive to and then die at age x' . Often, this is normalized to values in $[0, 1]$ over the age interval $[x, \infty]$. It is therefore expected that someone of the cohort of age x dies at $\int_x^\infty x' S(x, x')\mu(x')$. Following [Leksell and Rabl \(2001\)](#) one can set the remaining life expectancy at age x as the difference of the above integral and the age x , setting

$$LE(x) = \left(\int_x^\infty x' S(x, x')\mu(x') dx'\right) - x = \int_x^\infty S(x, x') dx'. \quad (3-9)$$

In this study the implementation of IOMLIFET ([IOM, 2013](#)) is utilized to conduct life-table calculations in the context of health impact assessment. Using the tool one can thereby determine the change of life expectancy due to changed mortality rates as a result of exposure to air pollution. The detailed functioning of the life-table calculation

implementation is explained in Miller and Hurley (2006). The original Excel-based model was reimplemented in the R programming language. It was extended to work with the RR boundaries provided in Table 3-7. For all countries the pollutant-specific LLE measured in Years of life lost (YOLL) per $\mu\text{g}/\text{m}^3$ pollution per year is determined.

Population data provided by the UN Population Division of the Department of Economics and Social Affairs (UN, 2015) were utilized. The data used are the mid-year (as of 1st of July) population of both sexes combined per country. Country-specific annual population estimates stratified by 5-year age groups (i.e. 0-4 years, 5-9 years, etc. up to 95-99 years, and 100+) are given. The data are estimates for the years 1950 to 2015 and projections for future years are given in 5-year steps until the year of 2100. There exist three variants of low, medium and high fertility. Data projected for 2030 is used at medium fertility rate and shows comparably low uncertainty (cf. Figure 3-19).

As an example, consider the RR coefficient as given in Table 3-7, say for instance for a

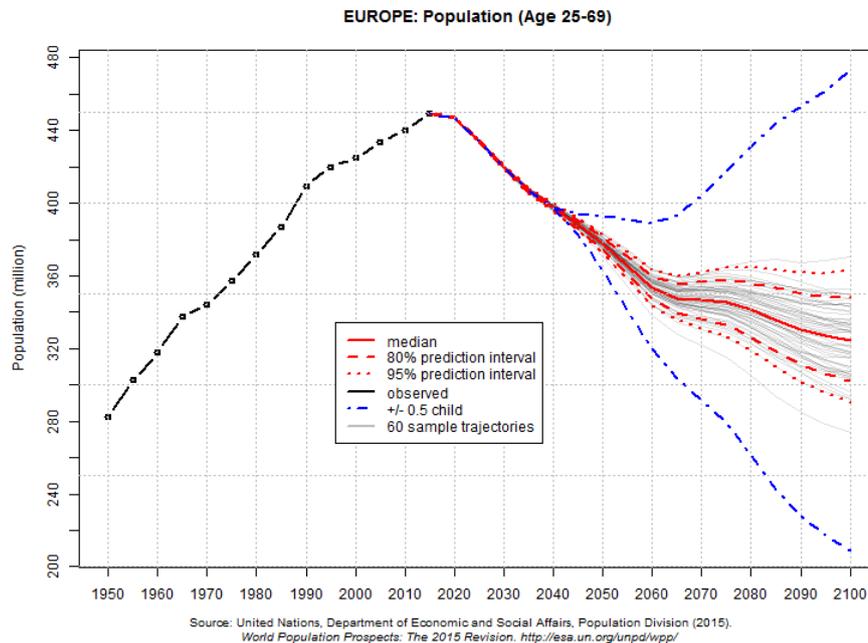


Figure 3-19: European population aged 25 to 69. Projection from 2015 onwards. Uncertainty remains very low until about 2040. The 95% CIs of the probabilistic projection are indicated by the red dotted lines.

RR of 1.062 per 10 $\mu\text{g}/\text{m}^3$ change in ambient PM2.5 concentration. The focus is on the effects of a 1 $\mu\text{g}/\text{m}^3$ reduction. The approach described in [Miller \(2013\)](#) is followed: A log-linear response curve is assumed, yielding an impact factor of $1.062^{(-1/10)} \approx 0.994$ ranging from about 0.992 (for RR of 1.083) to about 0.996 (for RR of 1.040). The factor is then applied to the age-specific 'natural hazard', i.e. the ratio of natural-cause deaths over the population of the given age-group.

These death rates are determined using age-stratified data from the WHO European mortality indicator database ([WHO, 2015](#)). Deaths from natural causes are considered, i.e. diseases under the 10th revision of the International Statistical Classification of Diseases and Related Health Problems (ICD-10) chapters I to XVIII (blocks A00 to R99), excluding chapters related to external causes (e.g. injuries or poisoning). The data are stratified by 15-year age groups (i.e. 0-14 years, 15-29 years, up to 60-74 years, and 75+ years). Data of the last year available are considered. The results (for medium fertility) of pollutant-specific LLE measured in YOLL per $\mu\text{g}/\text{m}^3$ pollution per year are shown in Table 3-9.

Given the specific RR for a certain health outcome, one can determine the impact function by multiplying RR with the specific background rate of disease for the affected population subgroup. Table 3-8 gives data on all-cause background mortality rate per 100,000 people taken from WHO's European mortality database ([WHO, 2015](#)).

When looking at the variability of the background rate across the years displayed in Table 3-8, there is a standard deviation of 5% in the EU counties, with Estonia being the highest at 10% and Italy showing least variance at 3%. Thus it is sensible to follow the suggestion of [Holland \(2014\)](#) and use the latest reported death rate per country in the calculations and estimate uncertainty by applying a 5% range following a triangular distribution.

3.4.2 Monetization of impacts

Monetary valuation is conducted differently for impacts which can be related to market prices (like crop shortfall due to pollution) and for impacts that affect non-market goods (like harming the physical integrity of a human life). Impacts for which market prices

Table 3-9: Country- and pollutant-specific reduction in life expectancy in 10^{-3} YOLLs per $1 \mu\text{g}/\text{m}^3$ change in ambient concentration. Life-table calculation was applied for estimated age distribution in the year 2030.

Country	PM2.5	NO ₂	O ₃
	RR=1.062 (1.040; 1.083)	RR=1.055 (1.031; 1.080)	RR=1.014 (1.005; 1.024)
Austria	1.616 (1.054; 2.141)	1.438 (0.820; 2.067)	0.374 (0.134; 0.637)
Belgium	1.630 (1.063; 2.160)	1.451 (0.827; 2.085)	0.377 (0.135; 0.643)
Bulgaria	1.632 (1.064; 2.163)	1.452 (0.828; 2.088)	0.377 (0.135; 0.643)
Croatia	1.643 (1.072; 2.178)	1.463 (0.834; 2.102)	0.380 (0.136; 0.648)
Cyprus	1.523 (0.993; 2.018)	1.355 (0.773; 1.948)	0.352 (0.126; 0.601)
Czech Republic	1.656 (1.080; 2.195)	1.474 (0.841; 2.118)	0.383 (0.137; 0.653)
Denmark	1.641 (1.070; 2.175)	1.461 (0.833; 2.099)	0.379 (0.136; 0.647)
Estonia	1.644 (1.072; 2.179)	1.463 (0.834; 2.103)	0.380 (0.136; 0.648)
Finland	1.666 (1.086; 2.207)	1.483 (0.846; 2.131)	0.385 (0.138; 0.657)
France	1.751 (1.141; 2.321)	1.558 (0.889; 2.240)	0.405 (0.145; 0.690)
Germany	1.638 (1.068; 2.171)	1.458 (0.832; 2.096)	0.379 (0.136; 0.646)
Greece	1.705 (1.112; 2.260)	1.517 (0.865; 2.181)	0.394 (0.141; 0.672)
Hungary	1.634 (1.066; 2.166)	1.455 (0.829; 2.091)	0.378 (0.136; 0.644)
Ireland	1.569 (1.023; 2.079)	1.396 (0.796; 2.007)	0.363 (0.13; 0.619)
Italy	1.864 (1.215; 2.471)	1.659 (0.946; 2.385)	0.431 (0.154; 0.735)
Latvia	1.615 (1.053; 2.141)	1.438 (0.820; 2.066)	0.373 (0.134; 0.637)
Lithuania	1.593 (1.039; 2.112)	1.418 (0.809; 2.038)	0.368 (0.132; 0.628)
Luxembourg	1.512 (0.986; 2.005)	1.346 (0.768; 1.935)	0.350 (0.125; 0.596)
Malta	1.603 (1.045; 2.124)	1.427 (0.814; 2.050)	0.371 (0.133; 0.632)
Netherlands	1.62 (1.057; 2.147)	1.442 (0.822; 2.073)	0.375 (0.134; 0.639)
Norway	1.576 (1.028; 2.089)	1.403 (0.800; 2.016)	0.364 (0.131; 0.622)
Poland	1.643 (1.072; 2.178)	1.463 (0.834; 2.102)	0.380 (0.136; 0.648)
Portugal	1.689 (1.102; 2.239)	1.504 (0.857; 2.161)	0.391 (0.140; 0.666)
Romania	1.612 (1.051; 2.137)	1.435 (0.818; 2.063)	0.373 (0.134; 0.636)
Slovakia	1.592 (1.038; 2.111)	1.417 (0.808; 2.037)	0.368 (0.132; 0.628)
Slovenia	1.617 (1.055; 2.143)	1.439 (0.821; 2.069)	0.374 (0.134; 0.638)
Spain	1.647 (1.074; 2.184)	1.466 (0.836; 2.108)	0.381 (0.137; 0.650)
Sweden	1.662 (1.084; 2.203)	1.480 (0.844; 2.127)	0.384 (0.138; 0.656)
Switzerland	1.605 (1.047; 2.127)	1.429 (0.815; 2.053)	0.371 (0.133; 0.633)
United Kingdom	1.644 (1.072; 2.179)	1.463 (0.835; 2.103)	0.380 (0.136; 0.648)

are available can be valued in a straightforward fashion. An often cited example for this are crop damages where market prices represent the value as if the crop was undamaged and sold instead. However, uncertainty arises from the fact that prices might be stated without full information and, to a likely much larger extent, present-time prices are stated while future monetary values have to be estimated. [Rabl et al. \(2014\)](#) estimate a GSD ranging from 1.1 to 1.3 due to the described sources of uncertainty but give no explanation for their reasoning. Another uncertainty may arise from the unknown potential for reduced crop losses by the development of more resistant species.

Impacts that affect non-traded goods are more difficult to value properly. In the context of this thesis special interest is on economic valuation of mortality and morbidity. Without doubt this is a good which is very difficult, if not impossible, to value on purely objective terms. [Rabl et al. \(2014\)](#) highlight the subjectivity of valuing mortality by discussing the variation in methodology and underlying data used by studies and suggest applying a meta-study with strict selection criteria whereas the authors state that an agreement on such criteria is hard to find.

Usually, studies on mortality have focused on value of prevented fatality (VPF) (or value of a statistical life (VSL)) rather than value of a life year (VOLY). In fact, the former is still used by many government agencies, although there are several valid arguments to use LLE based measures, like VOLY, instead. Air pollution is only a contributing cause for an individual death rather than a primary cause. Also, VPF estimates are based on fatal accidents when life expectancy is typically decreased by 30 to 40 years whereas premature deaths in Europe caused by air pollution reduce life expectancy only by about one half to one year. [Rabl \(2003\)](#) also argues that for air pollution most of the impact is not instantaneous but the cumulative result after years of exposure. Therefore, the total number of attributable deaths is not observable.

The ExternE methodology update ([Bickel and Friedrich, 2005](#)) recommends to use VOLY for valuation. The recommended value of €75,000 (ranging from about €27,000 to €225,000) was derived from VPF data using a conversion relationship between changes in probabilities of death and changes to life expectancy as established by [Rabl \(2001\)](#). This is almost log-normally distributed and it seems reasonable to assume a GSD of 3. In the scope of the NEEDS project [Desaigues et al. \(2007\)](#) evaluated results of a contingent

valuation questionnaire applied in nine European countries. The approach used by the authors is based on the change of life expectancy opposed to previous valuations of air pollution mortality that were based either on accidental deaths or on a small change in the probability of dying. The authors conclude that a central value of €40,000 ranging from €20,000 to €100,000 should be applied in the EU (cf. [Desaigues et al. \(2011\)](#)). Almost, log-normally distributed, this would imply a GSD of about 2.5.

VSL figures differ largely across regulatory agencies within a country: For instance, the US EPA estimates VSL at \$₂₀₀₀6.2 million while the US FAA uses \$₂₀₀₂3 million. The US Department of Transportation used to apply \$₂₀₀₂3,3 million which it recently changed to comply with the almost twice as high value used by the EPA. A recent meta-analysis of 850 estimates of studies across 38 countries around the world by [Lindhjem et al. \(2011\)](#) shows that the VSL measure also largely varies with the risk category analysed, namely environment, health and traffic. The authors report mean values of VSL as \$8.9 million, \$3.9 million, and \$6.8 million, respectively, and median values of \$3.0 million, \$1.1 million, and \$3.0 million, respectively. Based on this meta-analysis, [OECD \(2012\)](#) recommends a median VSL of \$₂₀₀₅2.9 million for OECD countries and \$₂₀₀₅3.6 million for EU countries.

3.5 Uncertainty of the impact and monetization of climate forcing gases

3.5.1 Uncertainty of the global warming potential

Although receiving a lot of attention in the last decade, the lack of scientific knowledge on future effects of climate change does not permit a detailed analysis of impacts. It is common though to estimate damages based on the amount of equivalent carbon dioxide (measured in CO₂-equivalent (CO₂eq)) emitted multiplied by the social cost of carbon (SCC). The CO₂ equivalence of some gas is determined by multiplying its mass by its global warming potential (GWP) for a given time horizon.

The GWP is defined by the IPCC as the time-integrated radiative forcing due to a pulse emission of a given component, relative to a pulse emission of an equal mass of CO₂.

It has usually been integrated over 20, 100 or 500 years. Over the past decades, it has become the default metric for transferring emissions of different (radiative forcing) gases to a common scale, here CO₂eq is the common scale.

The values differ over the years, and even though 100 years is the common metric, there is some debate about the appropriate time frame considered and in the most recent assessment report, AR5, the IPCC also provides values for 20 years (GWP₂₀) along with the values for 100 years (GWP₁₀₀). Also, there is some uncertainty attached to the GWP values that to the most extent stem from uncertainties in perturbation lifetimes, radiative efficiency, indirect effects and the absolute GWP for CO₂. The IPCC AR5 (IPCC, 2013) cites the multi-model study of Joos et al. (2013) which estimates uncertainties for the time-integrated radiative forcing of CO₂ to be ±15% and ±20% for a 20- and 100-year time horizon, respectively. The IPCC report estimates for a 20- and 100-year time horizon a CH₄ GWP uncertainty of ±30% and ±40%, respectively, for a 90% confidence interval. Methane has a relatively short lifetime of about 12 years. For GHG with a longer lifetime the uncertainty estimates are a little lower, namely ±20% and ±30% for a 20- and 100-year time horizon, respectively. These values apply for N₂O which has a lifetime of about 121 years.

3.5.2 Issues in valuing the impacts of climate change

There is only limited information on the true effects of rising temperatures due to climate change and research in estimating damages is rather scarce and difficult to conduct. Many estimates of the (marginal abatement) cost of a ton CO₂eq are usually based on the principle of an optimal solution at predefined limits of GHG concentrations in the atmosphere or a reduction of CO₂eq emissions relative to a past year chosen as a base or reference in political negotiations.

Rabl and van der Zwaan (2009) estimate the uncertainty in the cost of CO₂eq emissions based on a thorough review of cost estimated by Tol (2005). They conclude that a GSD of 5 is reasonable based on their findings but also state that the uncertainty range may well be larger. The uncertainty can be reduced by further research and the value of (improved) information is estimated in Rabl and van der Zwaan (2009), concluding that

research effort to improve the estimates may turn out to be extremely cost-effective.

The authors also note that there is a long tail associated with the log-normal distribution of the damage cost and the associated possibility of extreme climate events with small likelihood but very high costs. Thus, they conclude that possible gains from continued climate change damage cost analyses, i.e. climatic externalities studies, may be significantly higher than those obtained when increasing the understanding of the nature of abatement technologies and their prospected costs.

Recent studies aim to determine the damages caused by climate change and some of them aim to determine monetary values as well. Some authors disagree that carbon prices are adequate measures (e.g. [Palstev and Capros \(2013\)](#) among others).

3.5.3 Uncertainty of monetization

The social cost of a tonne CO₂-equivalent is even harder to determine and many approaches have been proposed when using SCC in integrated assessment modelling, for instance based on damage costs and based on avoidance costs. The methodologies have been briefly introduced earlier (see chapter 2.2.3). The influence of subjective quantities like equity weighting and discount rates have been determined by sensitivity analysis and were also discussed elsewhere (e.g. [Watkiss et al. \(2005\)](#)). Uncertainties associated with the marginal abatement costs of greenhouse gases have been discussed elsewhere, for instance in ([Anthoff et al., 2009](#)). Recommended mean [lower to upper] avoidance costs are given in [Schwermer et al. \(2012\)](#) as 251 [143 to 442] €₂₀₅₀/tCO₂eq which in turn is partly based on a meta-analysis of studies of the costs of GHG mitigation policies aiming at long-term stabilisation based on the results of 62 studies utilizing 26 different models ([Kuik et al., 2009](#)). Note, that discount rates have big influence on the SCC, that is utilizing an estimated discount rate of 3% yields 104 [59 to 182] €₂₀₂₀/tCO₂eq ([Schwermer et al., 2012](#)), whereas a discount rate of 5% yields 58 [33 to 102] €₂₀₂₀/tCO₂eq. The studies of the mentioned meta-analysis aim at different long-term stabilisation targets (mean of 611 ppm CO₂-eq) and different assumptions on economic parameters like growth, industry structure and technological developments. A significant (negative) effect on the costs is determined by the stabilisation target (see Fig. 3-20).

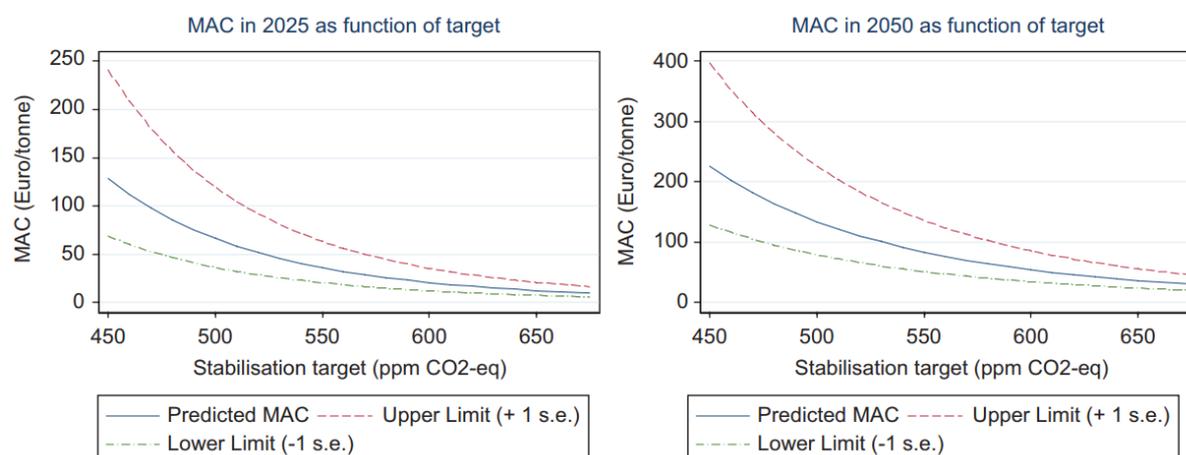


Figure 3-20: Marginal abatement costs as a convex function of implied stabilisation target (Source: [Kuik et al. \(2009\)](#)).

Note that the assessment of health impacts and climate effects cannot be separated but need to be integrated: By comparing the marginal avoidance costs for reaching the 2 degrees Celsius goal and the monetary value of a statistical life year lost, [Friedrich \(2010\)](#) estimates the impact of most climate change mitigation policies on environmental human health to be as important as the actual climate change effects. The author also notes that measures aiming at long-term reduction of CO₂ emissions, e.g. increased biomass utilization or better insulation of houses, cause negative short-term health effects. Also note that negative radiative forcing is induced due to aerosol-radiation interactions and aerosol-cloud interactions.

4 Policies eliciting behavioural change

Environmental data for the case study was collected and discussed in chapter 3. To meet the thesis objective both non-technical and technical measures are addressed. The latter will be discussed in chapter 5. The following deals with evidence-based estimation of response to policies when making use of non-technical options.

Given the context of the case study, the focus is on reviewing literature estimating the effect of policies in the field of transportation demand management (TDM). Several empirical studies have been conducted over the last decades to support policy making. Though conceptually akin, the effect determined in each study is associated with a certain error.

The field of transport economics has a long history of trying to synthesize evidence from these kind of studies. A description of the most influential past reviews in this field is given in chapter 4.1. Despite their wide-spread use these reviews lack some important characteristics which are needed for proper use in the context of this thesis. Note, for instance, that the studies have considerable spatial coverage but the focus has been traditionally on the US, the UK and Australia with some exceptions. Besides, some of the studies discussed within this chapter were conducted during more recent years while others appear less contemporary. Furthermore, several publications do not give proper indication of how the collected data have been reviewed and which criteria the underlying data had to fulfil, while others provide this information. However, the variance in the effect estimates of individual studies is likely linked to study specifics.

Thus, a consistent methodical approach is followed to synthesize empirical findings: Firstly, an extensive literature research is conducted in chapter 4.2. A vast body of studies is investigated resulting in the collection of almost 1,400 estimates. Care was taken to ensure that study specifics are noted and recorded in the resulting database. The intention is to overcome limitations with respect to transferability which are discussed in the beginning of chapter 4.3. Secondly, meta-regression analysis (MRA) is applied to address this issue. By applying MRA, pooled estimates can be induced to reduce the overall error estimating the effect of a policy. MRA is a method to conduct systematic literature reviews and derive quantitative findings from it. It is often used in the context of policy-relevant decisions in economics, social sciences, and medicine.

One may consider MRA an objective method to systematic review due to its statistically rigorous stance.

As a result, meta-regression models are developed and discussed to unravel the association between effect estimates and other characteristics. These characteristics include study-specific attributes but cover also additional data like gross domestic product (GDP) or population density which were collected from other sources and linked to the elasticity estimates. The individual models are presented in chapter 4.3.

4.1 Overview of past reviews on transport elasticities

A comprehensive literature review on transport elasticities was performed in the scope of this thesis. The following, however, introduces and summarizes the most influencing related reviews in the context of transport elasticities.

In 1980, the Transport and Road Research Laboratory of the UK Government, now named Transport Research Laboratory (TRL), published the so called *Black Book* (TRRL, 1980). The report deals with the demand for public transport. It establishes a number of standard elasticity values due to the ample scope of transport elasticities, variety of policy conclusions and comparably broad number of countries or regions considered, including Western European countries, North America, Australia and New Zealand. Findings of subsequent studies have over decades routinely been compared to and evaluated against this comprehensive source. At about the same time the US Department of Transportation published a handbook of travellers' response to transportation system changes with focus on nine topic areas documenting empirical findings of studies in the US. A first version was published in 1977 and an updated version four years later (Pratt et al., 1977; Pratt and Copple, 1981).

In the early years of the 1990s, three influential reviews of travel elasticities were published. Each covered or was considered representative for one of three major world region, namely North America (Oum et al., 1990), Europe (Goodwin, 1992) and Australia (Luk and Hepburn, 1993). The studies will briefly be introduced in the following paragraph. Oum et al. (1990) review estimates of the own price and mode-choice elasticity of demand

for several passenger and freight transport modes, covering also estimates on demand for gasoline along with cross-price elasticities mostly based on North American data. While the review itself is limited to estimates of price elasticities, the authors highlight that quality indicators of transport might be even more important than price, especially in freight transport and air travel. At about the same time a similar study was conducted by Goodwin (1991) with European focus, thus sharing very little data with the aforementioned study. However, more well known is the same author's study one year later with focus on European data, especially data collected in the UK (Goodwin, 1992). Special emphasis is on both short-term and long-term travellers' response to policies in individual motorized traffic and public transport. The review focuses on data of the late 1980s and early 1990s. The review by Luk and Hepburn (1993) for the Australian Road Research Board summarizes travel demand elasticities of the 1970s and 1980s in Australia. It covers elasticities of fuel consumption and traffic level with respect to petrol price, public transport demand changes due to fare changes or petrol price adjustments and freight demand response with respect to changes of road freight costs. The study found service level of public transport to be about three times as effective as price adjustments for inducing a modal shift from individual motorized traffic to using transit.

In the late 1990s and early 2000s several new or updated reviews have been published. The final report of the EC-funded project TRACE includes a comprehensive review of short- and long-run empirical findings and modelled estimates of time and cost elasticities. The authors state the intention to produce an elasticity handbook for an ex ante assessment of effects on auto-mobile travel demand at different transport planning levels. In the US, an interim handbook was published in 2000 by the Transit Cooperative Research Program (TCRP) and several minor reports on travellers' response to transportation system changes since about 2000. These are considered updates of the aforementioned handbook published in the 1980s (Pratt and Copple, 1981). The Bureau of Infrastructure, Transport and Regional Economics (BITRE) Transport Elasticities Database was established by the Australian Government in 1999. According to their website, the database contains about 200 bibliographic references and 400 table entries of empirical transport literature up to 2001 (BITRE, 2016). In the UK the *Black Book* data of the 1980 study (TRRL, 1980) was re-examined to reflect changed socio-economic conditions and new policy background (Balcombe et al., 2004). Goodwin et al. (2004) published a report

looking into elasticity estimates published since 1990 as one part of two blind literature reviews, the other one carried out by [Graham and Glaister \(2004\)](#). The latter study put more emphasis on freight transport. The authors of the former study state that the core results of both reviews are strongly consistent and the general results are broadly consistent though not in every respect.

In 2011, the Transport Research International Documentation (TRID) database of the US National Academies of Sciences, Engineering and Medicine was released. It provides about 90,000 references to free or fee-based documents on transportation research ([TRB, 2016](#)). It integrates records from the Transport Research Board (TRB)'s Transportation Research Information Service (TRIS) database and the Organisation for Economic Co-operation and Development (OECD)'s Joint Transport Research Centre's International Transport Research Documentation (ITRD) database. A collection of studies compiled by the private research organization Victoria Transport Policy Institute (VTPI) is available on the internet ([VTPI, 2014](#)). It lists numerous quantitative findings and provides guidelines on how to conduct TDM in different settings.

It is important to note that the aforementioned studies and other studies on elasticities referred to in this work are non-homogeneous and all of the empirical findings have to be considered imprecise and uncertain. Also, many of the data used in review studies substantially overlap. Many of the reviews use aggregated data of previous reviews (often by the same authors) and introduce new data that was collected since the publication or end of data collection phase of the previous review. Obviously, this renders aggregation of the data difficult due to their heterogeneous nature. A detailed MRA was conducted and the elasticities were linked to explanatory variables. The general usability and transferability of elasticities are discussed in more detail in chapter 4.3. There are differences in the specific type and definition of elasticities used in a study, namely point elasticities, mid-point arc elasticities, and shrinkage ratios. When no reference to the type of elasticity is given arc elasticities are commonly assumed.

4.2 Data collection of transport demand elasticities

There are inherent limitations in any literature review like the ones described in the previous chapter 4.1. Obviously, there is bias when selecting studies to conduct the review on. Furthermore, if reviews are considered, there might be a bias if publications are not part of the sources investigated. If they are, they may not be covered by the search terms defined in this review. Considerable effort was made to broaden the number of studies and data sources by including the largest databased accessible with a broad geographical coverage, and to make the queries to the databased as least narrow but still meaningful enough to derive sensible results.

Another source of potential bias exists that can neither be tackled nor can its uncertainties be quantified by this or any other review as one can only consider published literature. Obviously, all original literature investigated might be affected by publication bias, i.e. bias with regard to whether the results of academic research were likely to be published. This is a well-known phenomenon and has a desirable feature in a way that flawed or not-well designed studies are excluded by the peer-review process but it has an undesirable (and unquantifiable) feature, namely the tendency of researchers, reviewers and editors to prefer some outcomes that show only significant findings and do not publish (seemingly) less significant results.

However, due to the approach taken as described above, the results derived from this study reflect a broad number of studies and have considerable geographical and temporal coverage to draw meaningful conclusions and quantify uncertainties in a sensible way.

In this study, the sources listed below were investigated, resulting in a number of studies and meta-studies that had to be investigated individually. There exist three major sources that have been identified for the collection of data and references to studies in the field of transportation research, namely

- The Transport Research International Documentation (TRID) database of the US National Academies of Sciences, Engineering, and Medicine that provides about 90,000 references to free or fee-based documents on transportation research ([TRB, 2016](#)): It integrates records from two databases, namely

- the Transport Research Board (TRB)’s Transportation Research Information Service (TRIS) database, and
- the Organisation for Economic Co-operation and Development (OECD)’s Joint Transport Research Centre’s International Transport Research Documentation (ITRD) database.
- The Transport Elasticities Database maintained by the Bureau of Infrastructure, Transport and Regional Economics (BITRE) of the Australian government ([BITRE, 2016](#)): At the time of this study it contained 198 separate bibliographic references focusing on elasticities in the field of transportation, and holds a total of 396 table entries derived from these documents. However, the coverage of empirical transport literature is only up to 2001.
- The transportation demand management (TDM) Encyclopedia ([VTPI, 2014](#)) of the Victoria Transport Policy Institute, Canada: It is a resource of information on several transport demand management strategies and provides elasticities from several sources in the context of TDM planning and evaluation.

The databases were searched with a number of search queries that are described in Table 4-1. The separate searches resulted in 155 studies as a result of which 61 were excluded due to duplication, non-accessibility or irrelevance. From the remaining set of 99 studies it was possible to extract a total of 1,370 elasticity estimates.

The studies collected in this exercise span a considerable period of time. Figure 4-1 shows the historical data availability of transport elasticities estimates per major world region based on the collection period mentioned in the individual study. If a study spans a longer period, the median year was used in this depiction. If no specific period of data collection or observation was mentioned in a study, the publication date of the particular reference was used as an indicator instead. A majority of the studies was conducted from 1980 onwards with a decline since 2000. However, this does not necessarily imply a reduction in research on transport elasticities from 2000 onwards. In fact, as mentioned before the BITRE database, being an important data source for this study, only covers data up to the year 2001 (cf. chapter 4.1).

About one half (660) of the estimates are from studies conducted in urban or sub-urban

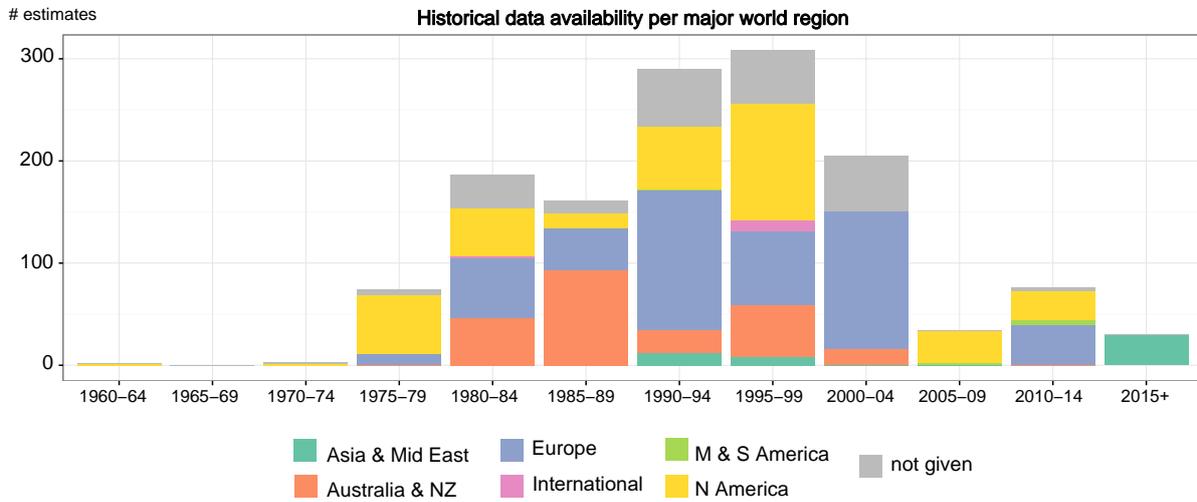


Figure 4-1: Historical data availability of transport elasticities estimates per major world region based on the collection period mentioned in the individual study. If the study spans a longer period, the median year was used. If no period was mentioned, the publication date was used instead.

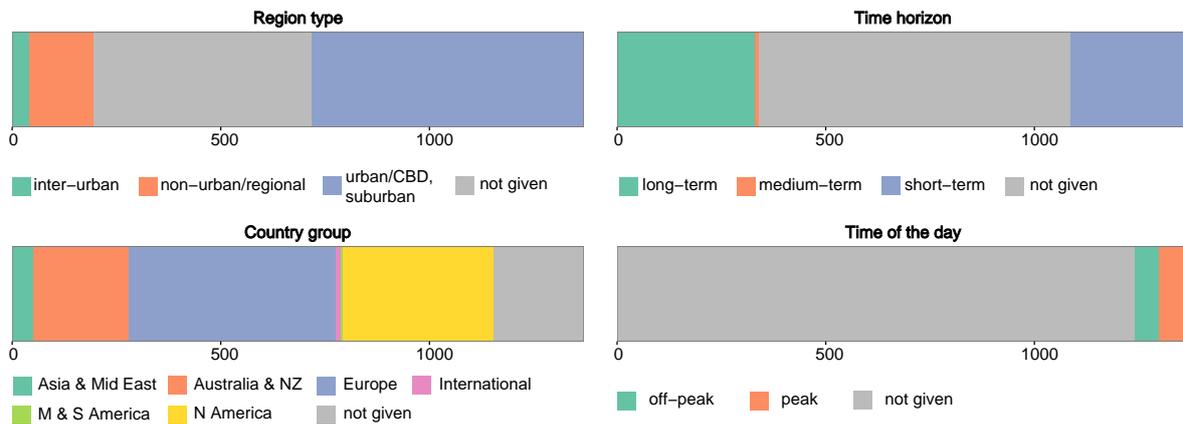


Figure 4-2: Overview of four important characteristics of the elasticity estimates derived from the studies investigated. The lack of complete information for each estimate calls for a method of imputing these data.

Table 4-1: Query terms used for literature review. BITRE allows either a search for any of the words or of an exact phrase only, whereas TRIS and ITRD allow logical AND- and OR-operators.

Query terms	Filter	Database	Studies
Any words: Fuel, Petrol, Diesel, Gasoline	-	BITRE	29
('fuel' OR 'petrol' OR 'diesel' OR 'gasoline')	English,	TRIS	24
AND ('elasticity' OR 'elasticities')	1950-2016		
('fuel' OR 'petrol' OR 'diesel' OR 'gasoline')	English,	ITRD	5
AND ('elasticity' OR 'elasticities')	1950-2016		
Any words: Bus, Coach, Train, Subway, Metro, Public	-	BITRE	51
('bus' OR 'coach' OR 'train' OR 'subway' OR 'metro' OR 'public')	English,	TRIS	11
AND ('fare' OR 'price' OR 'time' OR 'ticket')	1950-2016		
AND ('elasticity' OR 'elasticities')			
('bus' OR 'coach' OR 'train' OR 'subway' OR 'metro' OR 'public')	English,	ITRD	7
AND ('fare' OR 'price' OR 'time' OR 'ticket')	1950-2016		
AND ('elasticity' OR 'elasticities')			
Separate searches: Toll, Congestion, Road pricing	-	BITRE	9
('toll' OR 'congestion' OR 'road pricing')	English,	TRIS	9
AND ('elasticity' OR 'elasticities')	1950-2016		
('toll' OR 'congestion' OR 'road pricing')	English,	ITRD	9
AND ('elasticity' OR 'elasticities')	1950-2016		
Total study records returned			155
Excluded due to duplication, non-accessibility or irrelevance			61
Total studies in database			99
Total elasticity estimates in database			1,370

areas, whereas only every ninth estimate is specific to non-urban areas (154). The vast minority (47) specifically considers inter-urban travel. In 38% of the estimates (536) no specific region could be associated.

A little more than one third (36%) of the estimates was derived from studies conducted in Europe and about one in four estimates (26%) was taken from references investigating travel behaviour in the United States or Canada. Every sixth estimate (16%) is specific to studies from Australia or New Zealand. About 16% of the estimates were derived either using international data or there was no specific origin mentioned in the original study. 52 estimates (3.7%) stem from studies investigating data from Asia or the Middle East.

Information on the time-horizon was scarce in general and there is seldom information about the exact temporal horizon implied. Therefore, it is not evident as to whether the studies base their decision on same ground when categorizing estimates as short-, medium- or long-term. Even less information could be derived to distinguish elasticity estimates referring to peak hours and to off-peak hours. An overview of the described four important characteristics is given in Figure 4-2. It is recommended to use the provided information with caution when a distinction into time of the day or time-horizon is crucial.

4.3 Meta-regression models of transport policies

In the previous chapter data collection efforts with respect to transport demand elasticities are described. Often there is only limited evidence, especially for cross-elasticities. Consequently, the usability and transferability of empirical findings is limited. There are several pitfalls when applying transport elasticities in a context different from the one they were observed under. Nevertheless, this remains a widespread practice in studies using transport elasticities for policy support. However, applying elasticities from existing studies without appreciating the relative context of the evidence has the following shortcomings which may impact policy recommendation significantly:

- The majority of the studies and reviews on transport elasticities are several decades old while travellers' response to policy is known to change over time. For instance,

public transport demand change in response to fuel price adjustments is significantly correlated with the year of the reference of the elasticity value (cf. Table 4-2). The positive coefficient implies that people are nowadays more sensitive to fuel price changes as compared to the past and will likely become more sensitive in the future.

- Simple out-of-context application of literature findings ignores the fact that evidence was originally collected in different regions across the globe in which living conditions, travel distances and quality of transport alternatives may be significantly different from the policy-relevant location. For instance, evidence observed in the United States or Australia should not be carelessly applied in the European context due to different local value of owning a car and the different quality of rail-bound alternatives. In fact, population density and rail track length per area of land are significant predictors of the long-term change in public transport in response to fuel tax (cf. Table 4-2). Population density also is a significant predictor of the change in urban bus travel in response to rail-bound transport fares (cf. Table 4-3).
- Another shortcoming is the neglect of the impact of income or wealth on the estimated elasticity value. Hence, it is not surprising that another predictor of many transport demand elasticities, if not the most important one, is wealth measured as gross domestic product (GDP) per capita (cf. Tables 4-2, 4-3, 4-4 and 4-5).

For the above reasons it is not justifiable to apply existing estimates in different contexts without proper transfer into the new context. When the specific conditions are accounted for and are properly transferred into conditions of the policy context it seems reasonable to transfer elasticities into a different context. Therefore, the development and use of meta-regression models is proposed in this thesis. An overview about the data collected is given in chapter 4.2.

The aim is to synthesize literature and explain disparities among the results by using statistical analysis. Meta-regression analysis (MRA) is proposed to conduct such regression analysis on previously reported empirical findings of transport elasticities. It has a long history in economics and medical research as a tool to summarize and explain results of multiple studies. Care should be used as it is suggested to apply MRA in a low-dimensional settings by limiting the number of explanatory parameters ([Smith and Pattanayak, 2002](#)).

An extensive MRA is conducted and regression models are built with the aim to transfer findings on transport elasticities to other contexts, regions, and other times. Therefore, the following approach is applied to the findings of the literature review: In chapter 4.3 a MRA is conducted to (i) determine cross-elasticities of individual price components as opposed to total operating cost like the fuel price, toll cost, or ticket price, and (ii) implement regression models of cross-elasticities using specifics including wealth and income, attractiveness of alternative transportation systems, and population density. Subsequently, income-dependent elasticities are generated as described in chapter 4.4 to account for the different mobility behaviour of people of different socio-economic background. This is relevant to account for the known effect of travel inequality in which higher income groups tend to be less affected by price component changes of transport.

To determine meta-regression models the data from the studies was enriched by the following data:

- Real GDP data from the World Bank, adjusted for purchasing power - as a proxy for wealth development. Historical data from World Bank and United Nations (UN) were aligned with the year when the study was published or, if known, the references therein were published or, if known, the actual study data was collected.
- Population density data from the UN Department of Economic and Social Affairs' Population Division - as a proxy for degree of urbanization.
- Rail track length per area of the country - as a proxy for the service level and/or attractiveness of public transport services.

4.3.1 Fuel price: Effects on public transport demand

Car energy efficiency is comparably low, partly due to low occupancy rates. Thus, individual motorized traffic seems to be a low hanging fruit for avoiding environmental pollution but motorists usually associate a high level of utility to individual travel as opposed to using public transport. With respect to distance travelled fixed cost make up the majority of the annual total cost of ownership (TCO) of a car ranging from 70 to 75% of which depreciation contributes about one half to total cost. One may think that

this leaves little room for effective financial incentives to push passenger transport from individual motorized traffic towards public transport. However, often people are not fully aware or underestimate by a large extent the fixed cost of owning a vehicle.

A MRA of short- and long-term public transport demand cross-elasticities of fuel price based on the studies found was conducted. The coefficient, standard error and significance levels are given in Table 4-2. The models for short- and long-term demand both

Table 4-2: Coefficients of meta-regression model for short-term public transport demand cross-elasticity of fuel-price (for non-business purposes).

Variable	Coefficient (Std. Error)	t-value	p-value	
short-term (adj. R ² =0.90)				
GDP per cap., PPP [1000 Intl.-\$ ₂₀₁₁]	-0.0501 (0.0135)	-3.711	0.0048	**
Population density [1000 ppl/km ²]	0.7673 (0.4422)	1.735	0.1168	
Rail track length per area of land [km], logarithm	0.0584 (0.0376)	1.552	0.1552	
Year of reference	0.0011 (0.0002)	4.708	0.0011	**
long-term (adj. R ² =0.96)				
GDP per cap., PPP [1000 Intl.-\$ ₂₀₁₁]	-0.0705 (0.0366)	-1.927	0.0902	.
Population density [1000 ppl/km ²]	2.7601 (0.7464)	3.698	0.0061	**
Rail track length per area of land [km], logarithm	0.2877 (0.0350)	8.209	0.0000	***
Year of reference	0.0020 (0.0005)	3.776	0.0054	**

Significance codes: '***' \triangleq $p \leq 0.001$, '**' \triangleq $p \leq 0.00$, '*' \triangleq $p \leq 0.05$, '.' \triangleq $p \leq 0.1$

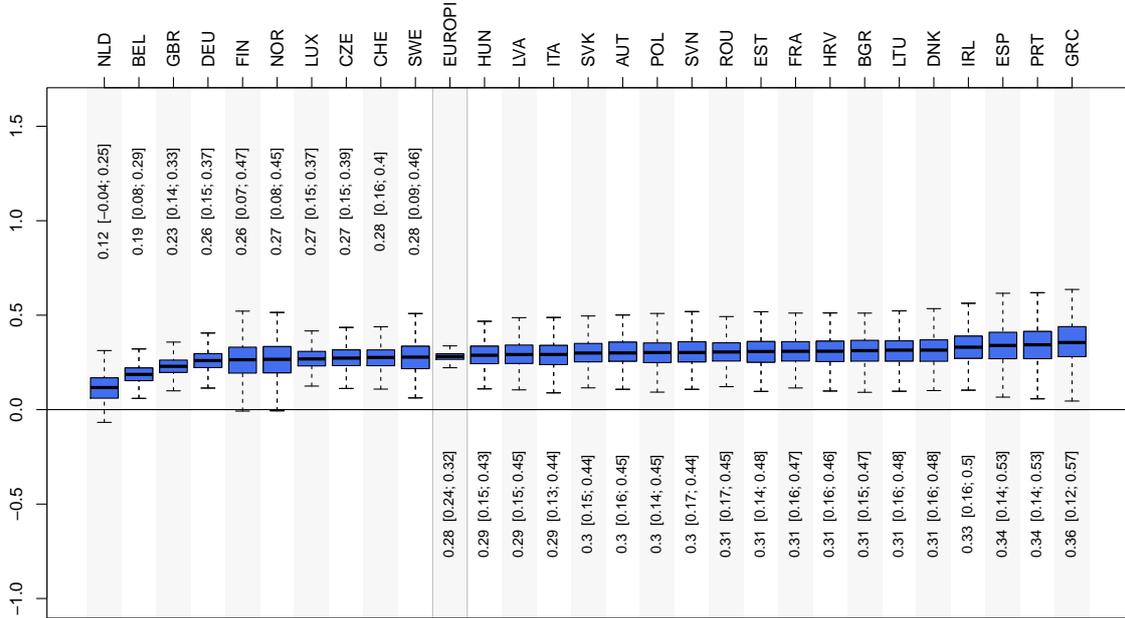


Figure 4-3: Country-specific short-term public transport demand cross-elasticity of fuel price as derived from the regression model as a function of wealth (GDPat PPP per capita), urbanization (population density) and attractiveness of public transport (rail kilometres per country area).

represent the underlying data very well (adjusted R^2 of 0.90 and 0.96, respectively). Also, the pattern of the coefficients are very similar though significance levels for individual coefficient differ. It can be concluded that, in general, the likelihood to shift modes towards public transport due to increased fuel prices: (i) decreases with increasing GDP per capita (i.e. wealth), (ii) increases with increasing population density (i.e. urbanization), (iii) increases with increasing public transport service level (i.e. attractiveness), and (iv) increases over time.

The above statements hold for both short-term and long-term demand changes. It is noteworthy, that the found evidence is quite intuitive as wealthier societies might choose private transport over public alternatives due to additional utility. Also, it seems obvious that increasing the attractiveness of public transport might draw people away from individual transport, as is shown by the model.

The country-specific short-term public transport demand cross-elasticity of fuel price as derived from the regression model is shown in Figure 4-3.

4.3.2 Urban bus fares: Effects on car travel and rail-bound public transport demand

Generally, the habit to shift from bus travel to private car travel due to increased bus fares is quite uncommon in urban areas. Instead of choosing individual transport options, it is generally observed that people more commonly move to an alternative mode of public transport, e.g. rail-bound transport, when bus fares increase. Thus the change in urban rail-bound travel demand due to increased bus fares was investigated. The coefficient of the meta-regression model along with the results are given in Table 4-3.

Regarding the effect on individual motorized traffic demand the main findings of the individual studies used for regression are described in the following. A total of 18 estimates from 9 individual studies is considered in this analysis spanning a time period from 1974

Table 4-3: Coefficients of meta-regression model for the logarithm of short-term urban car travel demand (non-business) and for short-term urban rail-bound transport demand cross-elasticity of bus fares (all purposes).

Variable	Coefficient (Std. Error)	t-value	p-value	
urban car travel (adj. $R^2=0.83$, p-value<0.0000 (***))				
GDP per cap., PPP [1000 Intl.-\$ ₂₀₁₁],	-0.1286 (0.0281)	-4.576	0.000	***
Rail track length per area of land [km], logarithm	0.2753 (0.2452)	1.123	0.282	
urban rail-bound travel (adj. $R^2=0.63$, p-value=0.0219 (*))				
GDP per cap., PPP [1000 Intl.-\$ ₂₀₁₁]	-0.0957 (0.0322)	-2.966	0.0251	*
Rail track length per area of land	-0.1879 (0.1906)	-0.985	0.3629	

Significance codes: '***' \triangleq $p \leq 0.001$, '**' \triangleq $p \leq 0.00$, '*' \triangleq $p \leq 0.05$, '.' \triangleq $p \leq 0.1$

until 1999. The studies include observations in Australia (including Sidney, Melbourne, Brisbane and Canberra), United Kingdom (including London) and the United States (including San Francisco). Three of the studies explicitly state the trip purpose as work or commute (McFadden, 1974; Luk and Hepburn, 1993; Taplin et al., 1997), while it is not possible to derive the specific trip purpose for the other findings. Note that only one study explicitly states the values to be short-term (Industry Commission, 1993), whereas the others do not mention the time horizon explicitly. Thus, long-term effects of urban bus fares are not modelled separately.

The review of Luk and Hepburn (1993) observes a small effect of public transport prices to reduce work trips conducted by individual transport. The corresponding cross-elasticity is 0.06. For all trips, IPART (1996) finds a much lower response of 0.005 as a response to bus fare increases in the same city. Industry Commission (1993) sticks out with a much higher general short-run elasticity suggestion of 1.01 for car travel demand due to an increase in bus fares in the same country. Also for Sidney, Dodgson (1985) and Taplin et al. (1999) find elasticities of 0.0072 and 0.036, respectively, in response to bus fare increases. Dodgson (1985) analyses the effects of bus fare increases across many cities in Australia, namely Sidney, Melbourne, Brisbane, Adelaide, Perth, Canberra and Hobart. They found private traffic elasticities ranging from 0.0035 in Brisbane to 0.0049 in Hobart.

In the United States (US), McFadden (1974) determines an elasticity 0.15 for San Francisco commuters in the 1970s and a slightly lower value (0.12) for all individual traffic in response to increases in urban bus fares. Nash (1982) finds that in the US inter-city car travel demand elasticity due to bus fare increases is at 0.05. Thus, at least in the US, the effect seems to be about two and a half times lower for inter-city than to urban travel.

For the UK, Acutt and Dodgson (1994) find a low value of only 0.005 for London where an earlier study refers to a higher value of 0.064 (Nash, 1982). Outside of London, the former authors find a higher elasticity of 0.0018 with respect to bus fare increases.

One may summarize that the increase in car travel demand was observed as generally very low by most of the studies. A more likely transport alternative that might be chosen when increasing bus fares is rail-bound public transport.

Regarding the effect on urban rail-bound transport demand the main findings of the individual studies used for regression are described in the following. In total 9 estimates from 3 individual studies are considered in the analysis spanning the same period as above. Again the geographical coverage is limited to Australia, the United States and the United Kingdom. Note, that train demand due to changes in coach fares (i.e. non-urban buses) is analysed in chapter 4.3.5.

[Nairn and Hooper \(1992\)](#) find for 1986 that train demand in Australia with respect to bus fares shows an elasticity of 0.4. [IPART \(1996\)](#) refers to lower change in rail-bound demand (0.009) in Sydney due to increased bus fares. [Taplin et al. \(1999\)](#) observe about twice the effect in the same city (0.019). [Taplin et al. \(1997\)](#) state an elasticity of 0.063 for urban commuters.

In London, [Gilbert and Jalilian \(1991\)](#) observe a short-run underground rail demand elasticity with respect to bus fares of 0.476 and almost twice the effect in the long-run (0.897). For general rail demand the authors find lower values of 0.082 in the short-term, and in the long-run more than twice the effect (0.193).

In the US, the study of [McFadden \(1974\)](#) finds a rail demand elasticity of 0.28 with respect to bus cost increases in San Francisco.

Though not specifically modelled here, a common finding is that people are by a factor of 2 more likely to change their mode of transport during off-peak hours than during peak hours (e.g. [Litman \(2004\)](#)).

Analysis of the regression model for urban car travel demand with respect to bus fare changes shows the following: The effect (i) decreases with increasing GDP (highly signif.) and (ii) increases with increasing rail network density (non-signif.).

Analysis of the regression model for urban rail-bound travel demand with respect to bus fare changes shows the following: The effect (i) decreases with increasing GDP (signif.) and (ii) also decreases with increasing rail network density (non-signif.).

The regression models were run for car demand and rail demand due to bus fare changes for all EU28 countries plus Norway and Switzerland. The results including uncertainty ranges as produced by the regression model are shown as per-country box-whisker plots

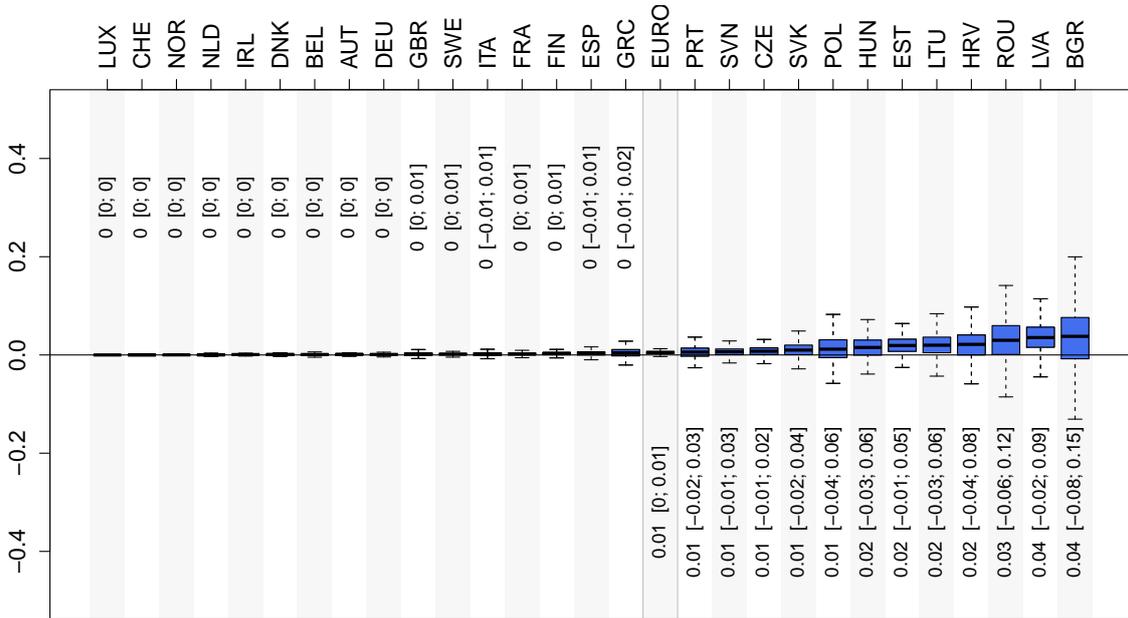


Figure 4-4: Country-specific car travel demand cross-elasticity of bus fares as derived from the regression model for urban areas.

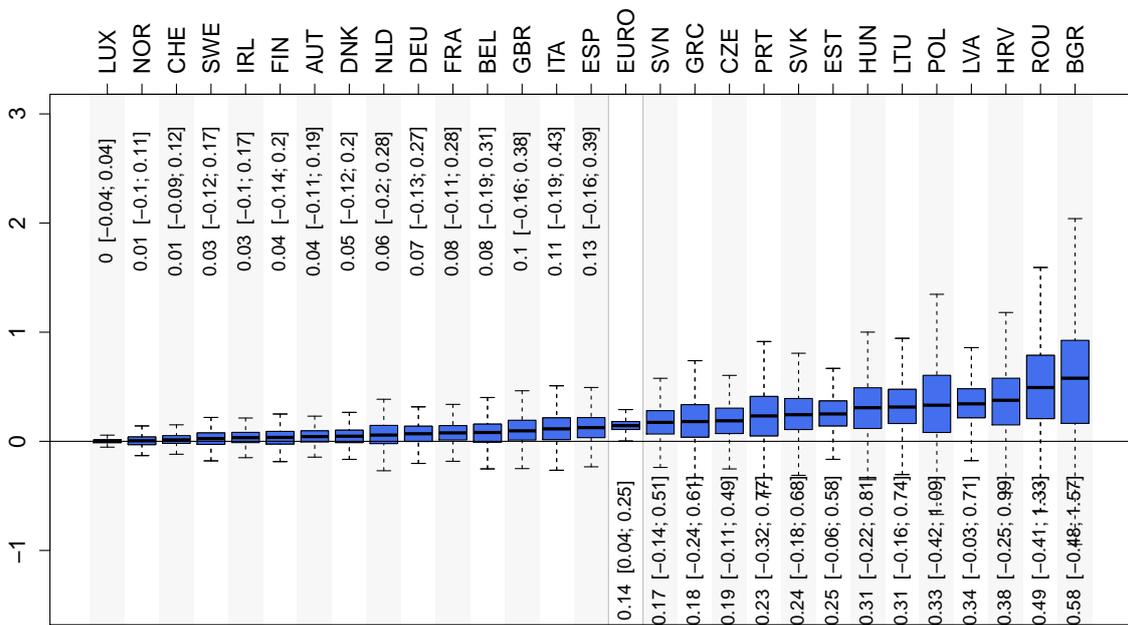


Figure 4-5: Country-specific rail-bound travel demand cross-elasticity of bus fares as derived from the regression model for urban areas.

in Figures 4-4 and 4-5. The kilometre-weighted average for the European region (EURO) is also depicted and is intended to serve as an average estimate. However, one should not be misled by the low uncertainty as this occurs only due to the averaging process.

One can clearly spot the impact of the country-level income (in terms of per capita GDP) and rail network density/quality (in terms of served rail-kilometre per are of land). For both models the high-income countries Luxembourg, Switzerland and Norway score best, indicating that bus passengers in these countries are unlikely to be affected by an increase in bus fares in a way they would consider a modal shift. Similarly, Bulgaria, Romania, Croatia and Latvia are ranked last in both models. The model result suggests, that bus passengers in these countries will more likely shift modes towards rail-bound transport when bus ticket prices increase. The mean sensitivity to bus fare increases in these countries is between 2 and 4 times higher than the European average, namely between 0.34 and 0.58 compared to 0.14. However, there is large uncertainty in these estimates which is depicted in Figures 4-4 and 4-5.

The same analysis was conducted for car- and bus-travel in response to changes of rail fare. The regression model and the findings are presented in the subsequent chapter 4.3.3.

4.3.3 Urban rail-bound transit fares: Effects on car travel and bus demand

In chapter 4.3.2 it was shown that bus passengers in a response to bus fare increases are more likely to stick with public transport, i.e. switch transport mode to rail-bound vehicles, and only a small portion shifts to individual transport by car. Similarly, travellers' response to increased rail-bound transit fares is likely to mostly induce an increased demand of bus travel compared to only a small increase in individual transport. In the following, the main findings are discussed with respect to literature that investigated travellers' response to increased urban rail-bound transit fares. Similar to the previous section two regression models are developed for individual travel and bus travel.

Regarding the effect on individual motorized traffic demand due to increased rail fares, the main findings of the individual studies used are as follows. A total of 27 estimates

Table 4-4: Coefficients of meta-regression model for the logarithm of short-term car travel demand and for the logarithm of short-term bus travel demand cross-elasticity of rail-bound transport fares (all purposes).

Variable	Coefficient (Std. Error)	t-value	p-value	
urban car travel (adj. $R^2=0.86$, p-value<0.0000 (***))				
GDP per cap., PPP [1,000 Intl.-\$ ₂₀₁₁], logarithm	-1.3589 (0.1654)	-8.214	0.0000	***
Rail track length per area of land [km], logarithm	-0.1652 (0.1760)	-0.939	0.3580	
urban bus travel (adj. $R^2=0.84$, p-value<0.0046 (**))				
GDP per cap., PPP [1,000 Intl.-\$ ₂₀₁₁] logarithm	-0.1439 (0.2645)	-0.544	0.6097	
Population density [1,000 people/km ²] logarithm	0.6563 (0.2421)	2.711	0.0422	*

Significance codes: '***' \triangleq $p \leq 0.001$, '**' \triangleq $p \leq 0.00$, '*' \triangleq $p \leq 0.05$, '.' \triangleq $p \leq 0.1$

from 9 studies was investigated spanning data from 1974 to 1999 from six countries, namely Australia, France, Germany, United Kingdom, United States and Japan.

[Luk and Hepburn \(1993\)](#) investigate data from Sydney in 1978 to determine an elasticity of work trips by car with respect to rail fares and found it to be at 0.09. The authors found lower values with respect to bus and rail fare combined at about 0.06. [IPART \(1996\)](#) finds lower values for Sydney at only 0.009.

[Acutt and Dodgson \(1994\)](#) determine a car travel elasticity with respect to London's underground rail fares at only 0.0006. People were found to switch to another public transport mode instead.

[Nash \(1982\)](#) determines that the car travel demand elasticity in Boston with respect to transit fares is at 0.14 compared to only 0.060 to 0.064 in the UK.

[Banister et al. \(1991\)](#) model response of car demand changes due to public transport fare changes in Dortmund (Germany), Leeds (UK) and Tokyo (Japan) determining values of 0.12, 0.14 and 0.09, respectively.

[Taplin et al. \(1999\)](#) find a general elasticity of 0.111 of car travel demand cross-elasticity of public transport fares with slightly lower value of 0.082 in Sidney for commuters and general car travel demand elasticity of 0.046 induced by train fare changes.

[Dodgson \(1985\)](#) determines that changes of general public transport fares induce higher car travel demand as oppose to only raising rail fares. This can be explained by travellers choosing an alternative mode of public transport when only rail fares are increased. The authors find values of 0.0119 for rail fares only in Sidney as opposed to 0.0191 when all public transport is affected. For other cities in Australia they found a similar pattern, namely 0.0039 and 0.077 in Melbourne, 0.0041 and 0.0075 in Brisbane, 0.0023 and 0.0078 in Adelaide and the highest difference of 0.0009 and 0.0051 in Perth.

Regarding the effect on urban bus demand due to increased rail fares, the main findings of the individual studies used are as follows. Spanning data from 1974 to 1999 from Australia, United Kingdom and the United States, a total of 8 estimates from 7 studies were analysed.

[Gilbert and Jalilian \(1991\)](#) reveal short-run bus demand elasticities with respect to underground rail fares in London to be 0.041 in the short run and 0.356 in the long-run. [Goodwin \(1992\)](#) estimates short-run bus demand elasticities with respect to underground rail fares in London at 0.2. The same author estimates long-run effects to be ranging from 0.3 to 0.6 based on the studies of [Gilbert and Jalilian \(1991\)](#) and [Fairhurst et al. \(1987\)](#).

[IPART \(1996\)](#) finds very low response in bus demand due to changes in rail fares at only 0.004 in Sidney. A later study of [Taplin et al. \(1999\)](#) estimates higher values of 0.016 for the same city. According to [Taplin et al. \(1997\)](#), values are higher for commuters at 0.032 with respect to train fares.

For the US, [McFadden \(1974\)](#) determines a higher bus demand cross-elasticity with respect to rail cost at 0.25 for San Francisco.

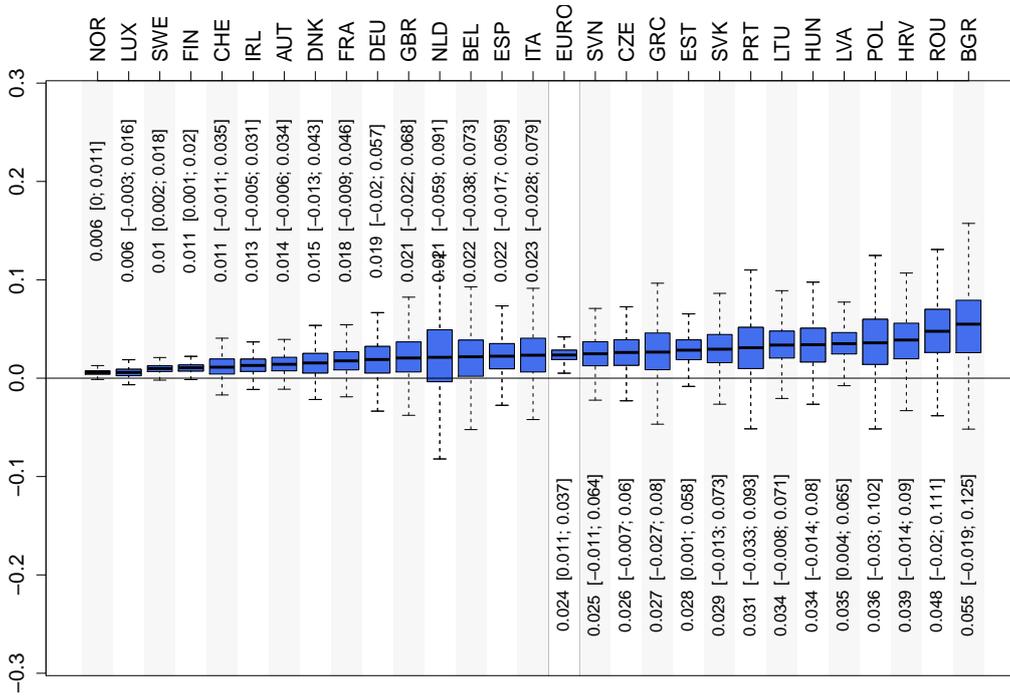


Figure 4-6: Country-specific urban car travel demand cross-elasticity of train fares as derived from the regression model.

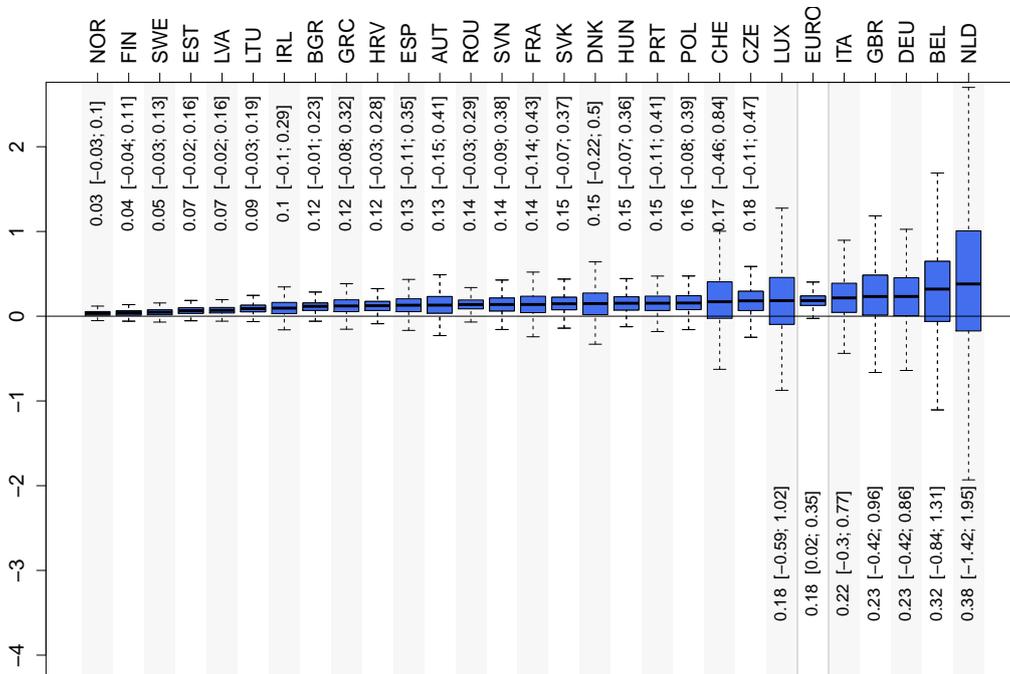


Figure 4-7: Country-specific urban bus travel demand cross-elasticity of train fares as derived from the regression model.

Analysis of the regression model for urban individual transport demand with respect to rail-bound transit fare changes shows the following: There is (i) strong and significantly negative correlation with income ($p < 10^{-4}$) and (ii) negative correlation with rail track density.

The analysis of the regression model for urban bus traffic demand with respect to train fare changes shows the following: It shows (i) strong positive correlation with population density ($p < 0.05$) and (ii) negative correlation with income. The respective coefficient are given in Table 4-4.

The regression models were utilized for car demand and rail demand due to bus fare changes for all EU28 countries plus Norway and Switzerland except Cyprus and Malta as there is no rail-bound passenger traffic on the two islands. The results are plotted in Figures 4-6 and 4-7.

4.3.4 Road pricing: Effects of city tolls on car travel demand and public transport

Recent studies indicate that auto-mobile travel tends to be quite sensitive to tolls (VTPI, 2014). While this makes road pricing attractive as policy instrument to reduce traffic on the one hand, policy-makers should, on the other hand, consider predicted revenues of toll projects with care. Also, it should be noted that due to a rebound effect vehicle travel after road pricing may increase when the revenue is used to fund capacity expansion.

Several types of road pricing schemes exist that can be implemented at various scales and provide different benefits and disadvantages. Scales can range from certain facilities only (e.g. toll roads or HOT lanes) over corridors and cordon (e.g. cordon fees or congestion pricing) to a regional scale that is paid for by the vehicle operator mostly on a distance-based scheme. Pricing methods for fee collection may vary as well: Pass, toll booth, electronic tolling, GPS devices or camera-based vehicle recognition.

The impacts on travel can be diverse. After pricing roads, travel can shift to free-of-charge routes, may lead to different destination choices or may induce a modal shift to transit or cycling (depending on the distance) or may induce ride-sharing. Obviously,

the amount of the shift induced depends on the quality of the service of the alternatives. Congestion pricing during peak hours may induce higher travel rates in off-peak periods.

The most prominent strategies are as follows:

- Fixed rates (road toll)
- Time-variable (congestion pricing)
- Cordon fees prices all road in a certain area, often implemented in the inner-city or in a central business district (CBD).
- Distance-based fees

[May and Milne \(2000\)](#) model the imposed effects due to separate implementation of different road pricing systems on travel demand in the city of Cambridge, UK. They investigate the traffic changes due to cordons crossed, distance travelled, time spent travelling and time spent in congestion. The authors find that charging per distance will yield non-linear impacts, namely a 5% reduction in total trips due to charging 10 pence per kilometre and twice the reduction for 20 pence, but only 15% for an almost quadrupled charge of 37 pence. [Brown et al. \(1993\)](#) also find a significant but declining effect of road pricing in the UK.

4.3.5 Non-urban train fares: Effects on non-urban car travel demand and coach demand

In the following the effects of train fares in the context of inter-city and general non-urban travel are investigated. One might expect that public transport alternatives in extra-urban context might be less attractive due to longer travel and transfer times when travellers need to consider changing the mode of transport. There is only limited evidence to properly model the cross-elasticity of coach travel demand with respect to changes in train fares. [Nairn and Hooper \(1992\)](#) find that in Australia the coach demand cross-elasticity with respect to rail fares is comparably high at 0.5. However, a generally high value is supported by findings on own-price elasticities of demand for coach travel: [Nairn and Hooper \(1992\)](#) determine an own-price elasticity of long-distance coach travel in

Table 4-5: Coefficients of meta-regression model for the logarithm of short-term non-urban car travel demand of rail-bound transit fares (all purposes).

Variable	Coefficient (Std. Error)	t-value	p-value
non-urban car travel (adj. $R^2=0.90$, p-value=0.0014 (**))			
GDP per cap., PPP [1,000 Intl.-\$ ₂₀₁₁], logarithm	-0.3482 (0.2602)	-1.338	0.2384
Rail track length per area of land [km], logarithm	0.5542 (0.2101)	2.638	0.0461 *

Significance codes: '***' \triangleq $p \leq 0.001$, '**' \triangleq $p \leq 0.00$, '*' \triangleq $p \leq 0.05$, '.' \triangleq $p \leq 0.1$

Australia of -1.3. Though being a rough assumption one may estimate a conversion factor from own-price elasticity to rail transit cross-elasticity of -0.38 using the aforementioned value found in the same study. The authors state that earlier studies find own-price coach demand elasticities in Australia ranging from -0.3 to -0.4. For regional travel which would roughly translate into 0.114 to 0.152.

Due to the lack of more detailed information on cross-elasticities the general coach demand cross-elasticity with respect to non-urban train fares is estimated using a uniform distribution from 0.1 to 0.5, representing the findings described above.

With regard to induced changes in car travel demand due to changes in train fares a total of 8 estimates from 5 studies from Australia, United Kingdom and the United States was investigated. All the studies were published in a comparably small time period between 1993 and 1997. The findings are as follows. [Hensher \(1996\)](#) uses a nested logit stated choice analysis to analyse pricing options in inter-city high-speed rail services between Sidney and Canberra. The study found cross-elasticity values ranging between 0.008 and 0.151 for non-business trips. [Industry Commission \(1993\)](#) determines an elasticity of car travel demand in Australia with respect to rail fares ranging from 0.04 to 0.19 in the short run. [Acutt and Dodgson \(1994\)](#) find for inter-city travel in the UK a value of 0.0118 and a lower value of 0.0022 for general regional travel. For the US, [Koshal et al. \(1996\)](#) find values at 0.0734 in the short-term and about two and a half times higher long-term effects

(0.1743). [Taplin et al. \(1997\)](#) determine a value of 0.37 for commuters.

The coefficients of the resulting regression model are given in Table 4-5. A visualization of the modelled effect of rail-bound transit fares on car travel demand are shown in Figure 4-8.

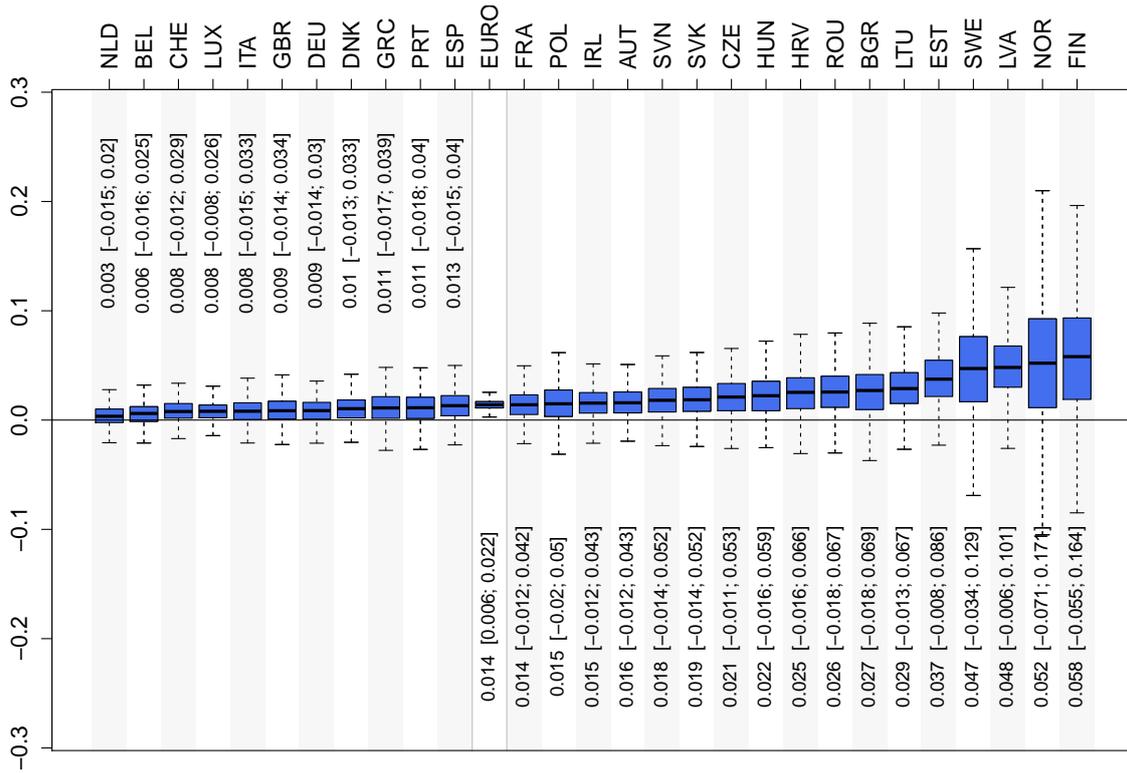


Figure 4-8: Non-urban individual travel cross-elasticity demand with respect to train fare.

4.3.6 Non-urban coach fares: Effects on non-urban individual motorized and rail-bound transit demand

The impacts of bus fares on individual and rail-bound public transport was investigated in the scope of urban regions in chapter 4.3.2. In the following the effects of adjusting fares of longer distance bus travel are examined. One might assume that rail-bound public

transport alternatives in extra-urban travel are generally more comfortable but also more costly than coach travel. Furthermore, individual motorized traffic by passenger car is more costly but might be favoured by some in terms of comfort as well.

However, aggressive pricing schemes in the coach sector have proven to attract a substantial amount of travellers from other alternatives. Consider Germany as an example: Until end of 2012 there were regulations in place that did not allow passenger transport within Germany by long-distance coaches. This was adjusted, so that from early 2013 onwards the ban is only valid for routes that are served by short-distance traffic as this would have an effect on state-subsidised transport. The liberalisation caused the emergence of a number of bus lines that offered long-distance passenger transport within Germany at rates that are very competitive to rail-bound passenger transport, the latter being almost completely served by a private joint-stock company with the Federal Republic of Germany being the single stakeholder.

There is only limited evidence available with respect to demand changes in other transport modes when fares of longer distance bus transport are changed. In the following the findings from studies that consider changes in car demand and changes in rail-bound transport demand in the extra-urban context are considered:

[Nash \(1982\)](#) finds inter-city car travel cross-elasticity with respect to bus fares to be at 0.05. As stated before in the analysis for the effects of fare price changes in urban bus travel, at least in the US, the effect seems to be about two and a half times lower for inter-city than to urban travel. [Taplin et al. \(1997\)](#) report similar results at 0.046.

[Nash \(1982\)](#) determines a negative effect for inter-city rail demand in the US at -0.834. Opposed to that, [Nairn and Hooper \(1992\)](#) determine that in Australia the train demand cross-elasticity with respect to coach fares is comparably high at 0.4 (with own-price elasticity of -0.43). The vice-versa finding (i.e. coach demand cross-elasticity with respect to train fares) is of the same magnitude at 0.5 (with own-price elasticity of -0.43).

[Taplin et al. \(1997\)](#) find that commuters' sensitivity to bus fares to be comparably low, expressed by a train demand cross-elasticity of bus fares at 0.063. It is interesting that for the vice-versa effect, i.e. bus demand cross-elasticity of train fares, the authors determined a five to six times higher value of 0.37 (also for commuters).

Due to the lack of information the uncertainty of the effect of non-urban rail-bound travel demand with respect to changes in bus cost was estimated using a triangular distribution with lower limit of -0.8, upper limit of 0.4 and a mode of 0.1 whereas the mode is derived from the value for commuters. Apparently, the effects of non-urban car travel demand in response to bus cost changes are about a factor of 2.5 lower than the effects in urban areas. This factor is applied to the results determined in chapter 4.3.3.

4.4 Income-dependent elasticity estimates

In the previous section it was laid out how literature-based findings can be transferred from the original context to a policy-relevant situation by developing meta-regression models. This enables to model cross-elasticity estimates based on characteristics including wealth, attractiveness of rail-bound alternatives and population density as a proxy of degree of urbanization.

However, few studies exist that stratify within-country cross-elasticities by socio-economic indicators like income, employment or level of education. Only a limited number of publications consider these effects. However, in general, it is well supported by several studies that people of different income will react differently to price changes.

Obviously, income is not the only socio-economic factor that influences travel behaviour and studies look into the socio-economic determinants of travel with respect to age (Lago et al., 1981; Terzis et al., 1995; Focas et al., 1998; Cervero, 1990), sex (Terzis et al., 1995; Focas et al., 1998), or employment (Goodwin and Williams, 1985).

Studies comparing wealth across countries found wealthy travellers to be less sensitive to price changes of travel demand of both private and public transport than low-income people (cf. e.g. Sterner et al. (1992), Brown et al. (1993), studies referenced in Schimek (1996), Johansson and Schipper (1997), Goodwin et al. (2004)).

In the US, Cervero (1990) finds – based on earlier studies – evidence that riders from families with low annual income (less than US-\$5,000) show a public transport own-price elasticity of -0.19 whereas those from families with higher annual income (more than US-\$15,000) show a lower elasticity of -0.28 indicating a higher rate of switching from

public transport to individual transport. The latter are more likely to have access to individual modes of transport as an alternative to public transport compared to the less wealthy.

Figures by [Collings and Lindsay \(1972\)](#) support this implication reporting that riders from households with cars show an elasticity of -0.10 with respect to public transport fares whereas those from households without cars show a four times higher elasticity of -0.41 . Work commuters in the San Francisco Bay Area show a small but positive car demand elasticity with respect to income (0.09) while the bus demand elasticity with respect to income is stronger and negative at -0.28 ([McFadden, 1974](#)).

[Johansson and Schipper \(1997\)](#) use a disaggregated model (12 OECD countries, 1973-1992) finding the long-run income elasticity of car travel demand to be 1.2 [0.65 to 1.25]. The authors state that this is mostly explained by an increase in car ownership having an income elasticity of 1.0 [0.75 to 1.25], and only to a lesser extent by an increase in mean driving distance found to have elasticity of 0.2 [-0.1 to 0.35] and some other minor factors.

An often-cited and more recent study of [Goodwin et al. \(2004\)](#) determines the income elasticity of total vehicle-kilometres to be 0.30 [0.05 to 0.62] in the short-run and 0.73 [0.12 to 1.47] in the long-run, as well as the income elasticity of vehicle stock to be slightly higher in both short and long run.

Unfortunately, a general indication of this relationship is not sufficient. The actual influence on price elasticities of demand are usually not distinguished into income groups.

One may conclude that push measures aiming to shift people from individual car traffic to transit are likely to disproportionately affect those of lower income. The model is designed to take account of the different response to component price change of lower income groups with respect to higher income groups. The World Bank provides data based on primary household survey data obtained from its country departments and from national statistical agencies. This includes annual data on the income share held by population quintiles in a specific country.

The nomenclature of chapter 2 is applied in the following. For a given income group I (e.g. income quintile) of a country C the income share is denoted by $\tau_{I,C} \in [0; 1]$.

The median income within a country is given by $\hat{\tau}_C$. If no data are given, this can be approximated by the middle quintile, for instance. Assume that the outcome of the meta-regression models is representative for the median group. The percentage change in quantity demanded of a given product due to a percentage change in income is reflected by the concept of the general income elasticity of demand which is denoted by E in the following. By the means of E one can estimate the income-specific cross-elasticities of an income group I by the following function:

$$\eta_{I,C,K,Q,K'} = \hat{\eta}_{C,K,Q,K'} \left(\frac{\tilde{\tau}_{I,C}}{\hat{\tau}_C} \right)^{-E} \quad (4-1)$$

where

$\eta_{I,C,K,Q,K'}$ is the cross-elasticity of demand of K' with respect to component Q of K specific to income group I in country C ,

$\hat{\eta}_{C,K,Q,K'}$ is the meta-regressed cross-elasticity of demand of K' with respect to component Q of K specific to country C ,

$\tilde{\tau}_{I,C}$ is the relative income share of income group I in country C ,

$\hat{\tau}_C$ is the median income in country C , and

E is the general income elasticity of demand.

Assume, for instance, the median income of a given country is € 40,000 and the upper quintile income is at € 85,000. At an income elasticity of 0.8 and at an assumed public transport demand cross-elasticity of fuel price of 0.3, one can determine the specific elasticity at $0.3(85/40)^{-0.8} \approx 0.16$. A lower income group with annual income of € 15,000 would have an estimated cross-elasticity of $0.3(15/40)^{-0.8} \approx 0.66$. This is in line with the aforementioned findings that low-income groups show higher sensitivity with respect to price changes.

5 Technical options and command-and-control regulations

Meta-regression models for policies aiming to induce behavioural change were developed in chapter 4. In this section technical options are considered. Results of their assessment in the scope of the case study are given in chapter 6.

In the light of WHO recommendation on exposure to NO_2 and the recent emissions scandal the focus of chapter 5.1 is on technical options that aim to reduce NO_x emissions from vehicle exhaust emissions. This includes the analysis of the use of modern selective catalytic reduction (SCR) systems as well as proposed software modifications. Furthermore, the impact of a scrapping bonus to support end-users in buying new vehicles when is assessed in chapter 5.2. The latter may become mandatory when retrofit options are not available and the reduction of urban NO_2 levels is pursued via low-emission zones (LEZs). Outside of these zones retrofitting remaining old diesel cars with diesel particulate filters (DPFs) is another option which is discussed in chapter 5.3.

5.1 Reduction of NO_x exhaust emissions

NO_x emissions are known to cause severe adverse health impacts worldwide ([Anenberg et al., 2017](#)) and its emission limits of diesel passenger cars have been lowered substantially by 84% from 500 mg/VKM for Euro 3 to 80 mg/VKM for Euro 6. To determine compliance to these limits – as well as limits of other emitted but regulated substances – the exhaust of passenger cars is investigated when type approval is requested. Up to the emission standard of Euro 6b, the New European Driving Cycle (NEDC) was used as a test cycle. The cycle is performed on a dynamometer and lasts for 1,180 seconds. About two third of the time a city-cycle is driven and one third is aiming to resemble non-urban conditions which is mostly characterized by higher driving speed. During the laboratory test the ambient temperature is regulated to be between 20 to 30 degree Celsius.

Recent investigations revealed the importance of reducing NO_x emissions from vehicle

exhaust emissions not only under stringent testing conditions but under more realistic daily-use conditions. For instance, [Carslaw et al. \(2011\)](#) show via vehicle remote sensing that real-world NO_x emissions from Euro 5 diesel cars remained about 4 times higher than the regulatory limits of 180 mg/VKM. Using a meta-analysis of previous portable emissions measurement system (PEMS) studies of Euro 6 diesel cars, [Franco et al. \(2014\)](#) find discrepancies between type-approval NO_x emissions and those during everyday operation estimated from real-world measurements. The authors found that on-road NO_x emissions from Euro 6 diesel vehicles tested were on average 7 times higher than the limits set by the regulation.

Car manufacturers and automotive suppliers have been accused of using a variety of devices whose software recognizes that a car is under test. It is suspected that under testing conditions the emission profile was adjusted with the intention to pretend that modern diesel cars would comply to stringent Euro 5 and Euro 6 emission standards whereas there are much higher non-complying emission rates under typical driving conditions.

From Euro 6c type approval onwards the Worldwide-harmonized Light-vehicles Test Cycle (WLTC) replaces the NEDC. The procedure is still a dynamometer test. Even though it can be considered an improvement over NEDC, a common critique of WLTC is that its acceleration patterns are unrealistically slow which affects the emission profiles. It is foreseen to determine real driving emissions (RDE) using a PEMS in on-street conditions as opposed to measuring on a dynamometer because some passenger cars are suspected to change their emission profile when test conditions are identified. Nevertheless, EU member states agreed in late 2015 to allow conformity factors (CFs) with respect to NO_x emissions. Under the WLTC, the following CFs are agreed on for type approval: From September 2017 onwards a CF of 2.1 and from January 2020 onwards a CF of 1.5, resulting in allowed violation of limits of 110% and 50%, respectively. For registration of cars, the CFs will apply from September 2019 and from January 2021 onwards, respectively. Note that these are not considered to be in effect in the reference case (cf. chapter 3).

There is an ongoing debate as to how reductions in NO_x emissions under daily-use conditions can be achieved in a cost-efficient manner. According to [UBA \(2017a\)](#), there are two major options, namely rolling out software patches to a large number of cars and retrofitting the car hardware with active SCR systems. While software patches have

comparably low individual cost per vehicle they have shown limited success in reducing NO_x emissions by only about 25% on average. Currently, there are no retrofit options for passenger cars available from manufacturers. However, a SCR prototype based on systems installed in light-duty or agricultural vehicles has been recently introduced by automotive supplier Baumot/TwinTec ([Baumot Group, 2017a,b](#)). The hardware retrofit system shows NO_x reduction of up to 95% not only on a dynamometer but also under RDE-like conditions ([ADAC, 2017a](#)). Details of both software and hardware option are analysed and described in the following sections 5.1.1 and 5.1.2.

5.1.1 Software patches for passenger cars and vans

Software patches are intended to cope with high NO_x emissions without changing the car hardware. They are intended to be installed by manufacturers onto cars that have already been sold during a visit at their respective service stations following a recall program. One of the aims of software modifications is enabling the NO_x abatement system to work at typical real-world temperature variations. The NEDC conditions prescribe a temperature window from 20 to 30 degree Celsius within which the exhaust emissions are measured. It has been shown that the systems installed in diesel passenger cars do not perform within the Euro 5 limits when the ambient temperature is outside of this window. [UBA \(2017a\)](#) estimates the necessity of the system to work at temperatures even below 10 degree Celsius. This is about the average annual temperature at traffic hotspots like Stuttgart Neckartor and temperatures can become much lower especially in Winter and during early peak hours of traffic.

Experts estimate a maximum of 50% reduction of NO_x emission as a result of software modifications given that the temperature windows are increased down to 10 degree Celsius and engine map is optimized ([UBA, 2017a](#)). However, this largely depends on the existence of necessary sensors and the performance and endurance of the exhaust after-treatment system. This affects the abatement potential and the number of vehicles that can be modified. Within the scope of a large mandatory recall program, the German manufacturer Volkswagen (VW) updated the software of about 2.3 million passenger cars which showed average NO_x reductions of 25% ranging from 2% to 45% ([UBA, 2017a](#)). These values were determined based on an adjusted NEDC with varying colder

Table 5-1: Abatement cost of software modifications for Euro 5 and Euro 6 diesel-fuelled passenger cars (PCs) and vans per 1,000 person-kilometre (PKM). Underlying assumptions are given in the text. Numbers in brackets represent 95% CI levels.

Vehicle category	Technology	Investment cost [€ ₂₀₁₀ /kPKM]	Operational cost [€ ₂₀₁₀ /kPKM]	Annuity ^a [€ ₂₀₁₀ /kPKM]
PCs	Euro 5 & 6 (Diesel-fuelled)	0.97 (0.76; 1.28)	0.96 (0.77; 1.22)	1.11 (0.90; 1.42)
Vans	Euro 5 & 6 (Diesel-fuelled)	0.74 (0.52; 0.93)	0.72 (0.58; 0.91)	0.84 (0.68; 1.06)

^a Interest rate $r = 0.3$, life-time $n = 7$ years. No stochastic behaviour for r and n assumed.

Table 5-2: Reduction potential of software modifications for Euro 5 and Euro 6 diesel-fuelled PCs and vans in 2030.

Vehicle category	Technology	Pollutant	Reduction [%] (direct)	Reduction [%] (fuel, up-stream)
PCs & Vans	Euro 5 & 6 (Diesel-fuelled)	NO _x	10.0 - 30.0	-3.0
		NM VOC, CH ₄	-	-3.0
		CO	-	-3.0
		CO ₂ , SO ₂	-3.0	-3.0
		PM ₁₀ , PM _{2.5}	-	-3.0

and warmer temperatures as well as using PEMS. However, these values should be considered estimates only as the measurements were not determined in an RDE-conform manner. According to car manufacturers only about 40 to 60% of the Euro 5 fleet could receive software updates. This is partly a result of the aforementioned limitations. [UBA \(2017a\)](#) estimates that this technical option may only reduce NO_x emissions by 10% assuming that only 40% of the Euro 5 cars receive an update and the abatement potential corresponds to the average of 25% measured within the fleet of recalled VW cars. Even at the highest estimate of 50% reduction and at the more optimistic application rate of

60% one can determine an upper bound of the reduction potential at 30%. The estimated reduction potential is summarized in Table 5-2.

The big advantage of this option, however, is its presumably low cost: [UBA \(2017a\)](#) estimates cost per vehicle in the lower three-digits. It is assumed in the following that the investment cost of software modification per passenger car is 150 [100 to 200] €₂₀₁₇ which corresponds to 136 [91 to 182] €₂₀₁₀. Annual mileage is estimated at 13,700 [9,000 to 18,000] vehicle-kilometre (VKM) with an average occupancy rate of 1.5 for PCs and 2 for vans. The respective cost values are given for passenger cars and vans in Table 5-1.

Following [ADAC \(2017a\)](#), an increase in fuel consumption of about 3% is assumed which also results in an increase of CO₂ and SO₂ emissions as well as up-stream emissions for fuel extraction, distribution and supply. Further, a fuel price of 0.6 [0.5 to 0.7] €₂₀₁₀ per litre and average fuel consumption of 7.5 [5 to 10] litres per 100 VKM is assumed, corresponding to about 150 PKM for passenger cars and about 200 PKM for vans. Investment cost per PKM is determined by dividing the per-vehicle cost by the product of lifetime and annual mileage.

5.1.2 BNO_x-SCR for passenger cars and vans

As aforementioned, car manufacturers have so far not offered retrofit NO_x abatement catalysts for diesel-fuelled cars that would enable them to comply to Euro 5 and Euro 6 emission standards. An independent retrofit prototype was introduced by automotive supplier Baumot/TwinTec. Even though the system does not have direct access to the engine map, promising results of about 90% reduction and beyond have been shown by [ADAC \(2017a\)](#) during test cycles and during real-world driving conditions. [Baumot Group \(2017a\)](#) claims that within the scope of a case study conducted by the Deutsche Umwelthilfe e. V. (DUH) reductions of 88.4% under WLTC conditions were achieved and 93.3% under real driving conditions were measured using a PEMS. In another case study about 95.3% reduction were measured under WLTC conditions and up to 98.8% reductions under highway driving conditions simulated on a dynamometer ([Baumot Group, 2017a](#); [ADAC, 2017a](#)). [ADAC \(2017a\)](#) estimate a 5% increase in fuel consumption due to increased usage of dynamo. The values are summarized in Table 5-4.

Table 5-3: Abatement cost of BNO_x-SCR system for Euro 5 and Euro 6 diesel-fuelled PCs and vans per 1,000 PKM. Underlying assumptions are given in the text. Numbers in brackets represent 95% CI levels.

Vehicle category	Technology	Investment cost [€ ₂₀₁₀ /kPKM]	Operational cost [€ ₂₀₁₀ /kPKM]	Annuity ^a [€ ₂₀₁₀ /kPKM]
PCs	Euro 5 & 6 (Diesel-fuelled)	14.08 (9.92; 20.66)	2.36 (1.93; 3.00)	4.62 (3.75; 5.82)
Vans	Euro 5 & 6 (Diesel-fuelled)	10.13 (8.15; 13.75)	1.78 (1.42; 2.24)	3.40 (2.82; 4.09)

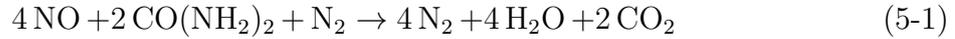
^a Interest rate $r = 0.3$, life-time $n = 7$ years. No stochastic behaviour for r and n assumed.

Table 5-4: Reduction potential of BNO_x-SCR system for Euro 5 and Euro 6 diesel-fuelled PCs and vans in 2030.

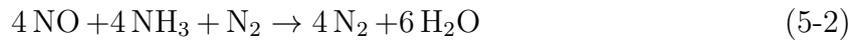
Vehicle category	Technology	Pollutant	Reduction [%] (direct)	Reduction [%] (fuel, up-stream)
PCs & Vans	Euro 5 & 6 (Diesel-fuelled)	NO _x	88.4 - 98.7	-5.0
		NM _{VOC} , CH ₄	-	-5.0
		CO	-	-5.0
		CO ₂ , SO ₂	-5.0	-5.0
		PM ₁₀ , PM _{2.5}	-	-5.0

The car part supplier claims to use mostly off-the-shelf parts to assemble the SCR system which makes a fleet-wide application at least possible apart from some limitations like available installation space. In the following the mechanics, limitations and foreseen costs are discussed. The reduction of NO_x to nitrogen (N₂) and water (H₂O) happens when the exhaust stream passes through the catalyst chamber. In a regular SCR system, the gaseous reductant NH₃ or urea are added to the exhaust gas stream. The reaction of

using urea ($\text{CO}(\text{NH}_2)_2$) to reduce NO_x emissions is as follows:



Leaving aside secondary reactions the main reactions of using ammonia (NH_3) for NO_x reduction are as follows:



The BNO_x-SCR system produces ammonia within a separate generator device outside of the main exhaust stream. Necessary heat is added from the partial flue gas flow and an extra electric heating device. The latter is needed for instance during the cold starting phase or when using a start-stop system. Ammonia is mixed into the main exhaust stream after the oxidation catalyst but before it enters the particulate filter and SCR catalyst. This arrangement reduces the process temperature to about 140-150 as opposed to 220 degree Celsius.

It is difficult to estimate the application rate in the whole car fleet as the system has so far only been installed in a mid-size family station wagon (VW Passat Variant, 1.6 TDI, Euro 5). There might be limitations in terms of applicability due to available installation space in parts of the passenger car fleet. According to [UBA \(2017a\)](#) the manufacturer questions the applicability to smaller cars and cars with rear-wheel or all-wheel drive. A large-scale collaboration with car manufacturers might be necessary. However, high application rates seem possible due to the use of existing off-the-shelf components: [ADAC \(2017a\)](#) lists system components consisting of a dosing system by BOSCH, an NH_3 generator with heating catalyst and sensors from Continental, along with original VW catalysts and particle filter.

The manufacturer estimates investment cost of 1,500-2,000 € per car (Baumot Group, 2017a,b). UBA (2017a) estimates the cost to be likely between 2,000 € and 2,500 € or even higher in some cases. One can, hence, assume an irregular triangular distribution of 2,000 [1,500 to 3,000] €₂₀₁₇ which translates to 1,819 [1,364 to 2,729] €₂₀₁₀.

AdBlue consumption for NO_x reduction varies across vehicle models and driving conditions. According to the German industry interest group Verband der Automobilindustrie e. V. (VDA), a passenger car will only consume an average of 1.5 litres per 1,000 VKM (VDA, 2013). This can be considered a lower bound on consumption. Dietsche and Reif (2014) estimate AdBlue consumption at about 5 [2 to 8] % of fuel consumption. Applying the average of 5% corresponds to 3.75 [2.5 to 5] litres per 1,000 VKM when assuming 7.5 [5 to 10] litres of diesel per 100 VKM. Measurements of ADAC (2017a) with the aforementioned BNOx-SCR system installed in a mid-size Euro 5 diesel passenger car determined consumption rates of 1.7 litres per 1,000 VKM when on a dynamometer and slightly higher rates of 1.9 litres per 1,000 VKM during RDE-like conditions. Considering all the above figures one may estimate consumption rates of 2 [1.5 to 4] litres per 1,000 VKM. AdBlue costs are estimated at 0.5 [0.4 to 0.6] € per litre. 7 to 8 years needed for amortization are stated by TwinTec (Baumot Group, 2017b). Again, investment cost per PKM are determined by dividing the per-vehicle cost by the product of lifetime ($n = 7$) and annual mileage. The cost estimates are summarized in Table 5-3.

5.1.3 BNOx-SCR for buses

The manufacturer of the BNOx-SCR system estimates investment cost for retrofitting buses at 12,000 € per system (Baumot Group, 2017b). It is claimed that also about 90% reduction in NO_x emissions can be achieved for buses as for passenger cars (cf. Table 5-4). Following Kugler (2012), the average annual mileage per bus is estimated at 24,400 VKM. Minimum and maximum deviation is assumed to be at one-third of the mean. Average occupancy rate of 16 persons per vehicle is derived from Figure 3-2 (see chapter 3). This yields an annual mileage of 382,589 [327,660 to 444,323] PKM.

Assuming an average fuel consumption of 3.55 times an ordinary passenger car (cf. Kugler (2012)) and an increase in fuel consumption of 5% due to enhanced dynamo usage as

Table 5-5: Abatement cost of BNOx-SCR system for Euro 5 and Euro 6 diesel-fuelled buses per 1,000 PKM. Underlying assumptions are given in the text. Numbers in brackets represent 95% CI levels.

Vehicle category	Technology	Investment cost [€ ₂₀₁₀ /kPKM]	Operational cost [€ ₂₀₁₀ /kPKM]	Annuity ^a [€ ₂₀₁₀ /kPKM]
Buses	Euro 5 & 6 (Diesel-fuelled)	4.65 (3.23; 6.69)	0.79 (0.63; 1.00)	1.53 (1.29; 1.90)

^a Interest rate $r = 0.3$, life-time $n = 7$ years. No stochastic behaviour for r and n assumed.

in chapter 5.1.2 along with the same relative increase of AdBlue consumption one can estimate operational cost and annuity of a BNOx-SCR system for buses as given in Table 5-5.

5.2 Ultra low-emission zones in cities along with a scrapping bonus

Banning specific car types from inner cities is debated in transport politics as well as in court. In general, LEZs are declared geographical areas with restricted access by vehicles which are considered more polluting than others. The aim is to improve air quality in these zones. However, this comes at the expense of end-users owning and operating vehicles that are banned from entering. Note, that this policy is different from previously discussed city tolls. The latter do not strictly restrict the entry of specific vehicles but aim to manage traffic by monetary means. The effect of city tolls on individual motorized traffic and public transport is investigated and quantified via meta-regression analysis (MRA) in chapter 4.3.4. Obviously, the two policies clearly affect each others outcome but are not mutually exclusive.

Throughout Europe several LEZs are already in place today covering urban areas in Belgium, Denmark, Germany, Italy, the Netherlands, Sweden and the United Kingdom.

In many places a phased introduction was carried out which affected different vehicles over time starting from the ones which were considered most polluting. The details of the implementation vary across countries and cities and usually evolves over time. The prominent cases of London and Stuttgart will be described in the following.

Almost the entire Greater London area was declared a LEZ which came into effect in 2008 initially targeting heavy-duty vehicles which did not comply to Euro 3 emission standard. Currently, the scheme has been tightened resulting in lorries, buses and coaches having to meet Euro 4 emission standard. In late 2017, a so-called toxicity charge ('T-charge') was introduced: In central London, cars and vans that do not comply to Euro 4 standards are charged an additional £10 on top of the congestion charge which is in place in a defined congestion charge zone (CCZ). An ultra-low emission zone (ULEZ) was announced by the mayor of London to be established from 2020 onwards. Within this zone charges of £12.50 per day for cars, vans and motorbikes were announced along with a charge of £100 a day for buses, coaches and lorries.

The city of Stuttgart introduced a LEZ ('environmental zone') in early 2008. Only minor exceptions were made including highways passing through the area. It is only allowed to drive in marked zones when a specific pollution badge provided by authorities is attached to the windscreen of the vehicle. Like in several other cities throughout Germany several stages of banning polluting vehicles have been applied. Currently, vehicles not meeting Euro 4 emission standard are not allowed to enter the LEZ. In July 2017, the administrative court ruled according to the intentions of the suing DUH against the federal state of Baden-Württemberg ([Verwaltungsgericht Stuttgart, 2017](#)). As a result the existing clean air plan of the city has to be enhanced with the aim to comply to ambient air quality standard, especially to immission limits of NO₂ and PM. According to [Verwaltungsgericht Stuttgart \(2017\)](#), an expert assessment found a more strict LEZ to be the only effective of the assessed policies: Such policy bans petrol-fuelled and gas-powered vehicles not meeting Euro 3 emission standard along with diesel-fuelled vehicles not complying to Euro 6/VI emission standard. In the remainder of this thesis such zones are referred to as 'blue' zones.

The policy is to a large extent targeted at NO_x emission reduction from diesel-fuelled vehicles and may be adopted by other cities throughout Germany also sued by DUH.

Table 5-6: Cost of replacing an existing vehicle with a new Euro 6 RDE-conform diesel PC or van per 1,000 PKM. Underlying assumptions including a scrapping bonus reduction are given in the text. Numbers in brackets represent 95% CI levels.

Vehicle category	Technology	Investment cost [€ ₂₀₁₀ /kPKM]	Operational cost [€ ₂₀₁₀ /kPKM]	Annuity ^a [€ ₂₀₁₀ /kPKM]
PCs	pre-Euro 5 (Diesel)	185.34 (144.34; 234.07)	-21.29 (-24.57; -18.70)	5.11 (-3.06; 13.25)
Vans	pre-Euro 5 (Diesel)	140.52 (107.51; 187.65)	-16.60 (-18.58; -14.77)	3.42 (-1.23; 9.74)

^a Interest rate $r = 0.3$, life-time $n = 8$ years. No stochastic behaviour for r and n assumed.

In general, reaction to LEZs as a policy is manifold. As one may envision LEZs being established in all urban areas throughout the European Union in the future, the focus of the following is on two major reactions observed: On the one hand people may switch to public transportation instead of utilizing individual travel which induces loss of utility. On the other hand it may potentially be more cost-efficient for people to acquire a less polluting car instead. In 2017, several car manufacturers offer discounts in Germany when bringing an old diesel car, irrespective of its brand, if customers buy replacement cars complying to Euro 6 emission standard. The offers range from about 2,000 to 10,000 € with averages around 4,000 to 6,000 € and tend to be higher for family cars and sport utility vehicles (SUVs) ([ADAC, 2017c](#)).

If people decide to buy a new car instead of using public transport alternatives or the aforementioned technical options, it is assumed that a 3,000 € scrapping bonus is offered by car manufacturers for vehicles that comply to Euro 6 when measured using a PEMS under RDE conditions. The figure is justified by the fact that only one major car manufacturer currently blamed offer high scrapping bonuses of 5,000 € for medium size whereas others being less in focus offer substantially lower discounts (around 2,000 to 3,000 €). Note that not all manufacturers offer such discount.

Investment cost for a new car is taken from a list of the most cost-efficient diesel-fuelled

cars (ADAC, 2017b). The annuity is determined assuming a lifetime of 8 years after which the remaining value of the vehicles is reduced by 80 [75 to 85] %. The value of the old car is covered by the discount provided by manufacturers.

The respective difference in operational cost is specifically difficult to estimate as it depends on both the new vehicle and the vehicle to be scrapped. It is assumed that additional cost for operating the SCR system is little compared to savings as a result of better fuel efficiency and saving due to less maintenance cost of the newly bought car. In total, it is estimated that the previous car had on average 5 [0 to 15] % higher running cost than the new one. The new car is assumed to have on average the operational cost of the top ten most efficient diesel cars listed in ADAC (2017b). The resulting cost figures are given in Table 5-6.

The scrapping bonus is implemented as an option that can be chosen by the optimization algorithm in case it turns out to be cost-efficient. The vehicles most heavily affected when aforementioned 'blue zones' are enforced are the ones with diesel-fuelled engines not complying to Euro 6/VI emission standard. People can then switch modes, i.e. use public transportation systems, or drive a compliant car. The cost-efficiency of this option compared to software or hardware retrofit options are assessed in chapter 6.3 of this thesis.

5.3 Retrofitting particulate filters

Exhaust from diesel cars was notoriously containing higher amount of particulates compared to petrol-fuelled counterparts because of the engine operating at higher temperatures and pressures. In chapter 5.2 the installation of so-called 'blue' zones was discussed which forbid entry for Euro 4 and pre-Euro 4 passenger cars and vans in cities. This may come at a heavy expense for the end-user if he or she does not switch modes towards public transportation systems. The policy focuses on urban areas for two major reasons: (i) dense population and high concentrations in urban areas imply high external cost in these regions, and (ii) the number of people that high costs are implied on is limited. As a result, older diesel cars are still allowed in non-urban areas. To tackle at least health effects from particulate matter which is possible at quite low cost by installing a DPF this measure is introduced here.

Nowadays, particulate filters are well-established in newly built diesel cars. The filters come in two major variants, namely wall flow filters and flow-through filters. The former are more effective and are the preferred variant in newly built cars whereas the latter are more popular for retrofit. In flow-through filters the exhaust is forced to flow through a filter medium of high surface area. They are mostly built from different types of ceramic or metal fibres. Fibrous filters usually produce lower back pressure than wall flow filters. However, their efficiency of removing particles is usually lower than those of wall flow filters.

The continuous flow of soot particles into the medium would eventually clog the filter. Therefore, it is a common procedure to burn off the collected particulates on a regular regeneration scheme. The process re-establishes the filter properties but induces additional carbon dioxide emissions during the process. However, this amounts to less than 1% of total CO₂ emissions.

As aforementioned wall filters achieve very high removal efficiencies of 95% and higher. Open retrofit filters, however, remove much less of the particles from the exhaust gas. Within a research project funded by the Federal Environment Agency of Germany, Umweltbundesamt (UBA), [Czerwinski et al. \(2007\)](#) investigated measurement campaigns with several retrofit particle filters ([Kugler, 2012](#)). They provide conclusions for a combination of DPF and diesel oxidation catalyst (DOC) and find particle emissions reductions of 31%. Also, carbon monoxide reductions of 40,5% are achieved while hydrocarbon emissions are reduced by 62,5% on average. Assuming an application rate of 90% in 2030 ([Kugler \(2012\)](#) assumed 50% in 2010 and 67% in 2015) the reduction potential is given in Table 5-7.

The investment cost for a retrofit filter are estimated at 647 €₂₀₁₀ including installation but without considering any potential state subsidies ([Kugler, 2012](#)). One major advantage of the filter is being maintenance-free. However, there are some minor operational cost due to increased fuel consumption. Fuel price of 0.6 [0.5 to 0.7] €₂₀₁₀ per litre and average fuel consumption of 7.5 [5 to 10] litres per 100 VKM are assumed (corresponding to about 150 PKM for passenger cars and about 200 PKM for vans). Annual mileage is estimated at 13,700 [9,000 to 18,000] VKM. The annuity is given in Table 5-8.

Public diesel-fuelled buses have been retrofit with a continuously regenerating trap (CRT)

Table 5-7: Reduction potential of diesel particle catalyst for pre-Euro 4 diesel-fuelled PCs and vans in 2030.

Vehicle category	Technology	Pollutant	Reduction [%] (direct)	Reduction [%] (fuel, up-stream)
PCs & Vans	pre-Euro 4 (Diesel-fuelled)	PM ₁₀ , PM _{2.5}	31,0	-1,0
		NMVOC, CH ₄	62,5	-1,0
		CO	40,5	-1,0
		CO ₂ , SO ₂	-1,0	-1,0
		NO _x	-	-1,0

Table 5-8: Abatement cost of diesel particle catalyst for PCs and vans per 1,000 PKM. Underlying assumptions are given in the text. Numbers in brackets represent 95% CI levels.

Vehicle category	Technology	Investment cost [€ ₂₀₁₀ /kPKM]	Operational cost [€ ₂₀₁₀ /kPKM]	Annuity ^a [€ ₂₀₁₀ /kPKM]
PCs	pre-Euro 4 (Diesel-fuelled)	4.72 (3.64; 5.79)	0.32 (0.26; 0.41)	1.08 (0.88; 1.30)
Vans	pre-Euro 4 (Diesel-fuelled)	3.54 (2.73; 4.34)	0.24 (0.19; 0.30)	0.81 (0.66; 0.97)

^a Interest rate $r = 0.3$, life-time $n = 7$ years. No stochastic behaviour for r and n assumed.

system in many European cities. The system combines particulate filters with an oxidation catalyst for continuous filter regeneration. The oxidation catalyst oxidises hydrocarbons and CO yielding CO₂ and water as well as oxidising nitrogen monoxide to NO₂. Afterwards, the nitrogen dioxide enters the particle filter and oxidises the collected particles. The CRT system not only reduces direct particle emissions by about 90% but also CO and volatile organic compound (VOC) emissions by also 90% (Kugler, 2012). However, excess NO₂ produced in the oxidation catalyst which has not been used to oxidise particles afterwards will be emitted via the exhaust stream. Adding an SCR to the system will solve this issue (cf. chapter 5.1).

Part III

Results

6 Results and discussion

The results of a case study in the context of the European passenger transport are presented in this chapter. Apart from answering policy questions these were selected to showcase the major features of the approach developed in this thesis.

Some general remarks on conjoint assessment of multiple policies as opposed to single measure evaluation are made in chapter 6.1. Implementation details with respect to the modelling language used are given at the end of the same chapter. To frame the scope of the case study, several scenarios to be analysed are outlined in chapter 6.2. The scenarios were selected to represent different parameter settings along with different constraints implied on the optimization approach. One may interpret these settings as having been chosen by a decision-maker to assess the variation across model outcomes for future policy scenarios and the sensitivity of responses to potential legislation.

In particular, it was decided to analyse the influence of several NO_x reduction goals in the light of the recent emissions scandal in chapter 6.3. Furthermore, the sensitivity of the model outcome with respect to a policy-maker's attitude towards risk is addressed. It is investigated in chapter 6.4 how moving from a risk-neutral to a risk-averse stance affects cost-efficiency of policy decisions.

6.1 General remarks

To be able to interpret the model outcomes it is first and foremost important to recognize that the integrated optimization approach developed in this thesis is able to deal with policy interactions and the interplay of behavioural responses and technical measures taken. These effects have been widely recognized as important in integrated assessment modelling (IAM) as they have substantial effect on policy-decisions (Sternhufvud et al., 2006). Consequently, it becomes possible to assess the combined effect of multiple policy instruments and technical options in a single analysis. This is obviously different from interpreting the assessment of single measures and deriving conclusions for proper portfolio generation of policies and measures as has been the standard in previous studies

(cf. e.g. [Kugler \(2012\)](#), [Friedrich et al. \(2015\)](#), [Friedrich and Schieberle \(2015\)](#)). In fact, these interactions have been broadly ignored and not properly accounted for due to the complexity of properly representing these effects in a modelling framework.

However, due to the existence of interdependencies between policies and measures it is not possible to attribute positive or negative effects to individual measures in a straightforward manner after conjoint application. This is a result of the fact that the impact of an individual measure depends on whether another policy was implemented or other options were considered: Take for instance the effect of additional fuel taxes which intends to induce modal shift of a portion of individual travel towards public transportation. Obviously, the magnitude of the impact of such policy depends – next to other parameters – to a large extent on the environmental friendliness of both individual and public transport. As aforementioned previous studies have estimated the effect on an isolated per-measure basis relative to the reference case. While the advantage of such approaches is their simplicity the estimation is likely overrating the positive impacts of individual measures as their effect is likely to reduce when other measures are taken simultaneously. Going back to the previous example involving fuel tax adjustments: When other measures are taken, for instance applying software patches to diesel cars, the environmental profile of individual traffic changes and the estimated impact of an increased fuel tax varies with it. Cars then become more eco-friendly and the advantages of public transport systems decrease. An analogue situation may occur when simultaneously public transportation systems are adjusted, say by retrofitting selective catalytic reduction (SCR) systems to city buses. In that case, however, other technical options to retrofit passenger cars (PCs) might also become more viable. It becomes evident that even in this simplified example it is not possible to attribute individual contributions of single policies and measures as if they were taken in an isolated manner. One might propose that the optimization approach should be run with individual policies or measures only, i.e. excluding the application of all but one single policy or measure, and this could be repeated for all individual measures. However, for the aforementioned reasons, the individual outcome is almost certainly different from the effect of that same measure when considered under conjoint application. This approach would be misleading and, hence, falls short of providing proper individual contributions of policies and measures. As a result the combined outcome has to be interpreted.

The methodology and the developed formulation are described in more detail in chapter 2. Technically, the approach was implemented using the Stochastic Programming (SP) feature of the Extended Mathematical Programming (EMP) framework for the General Algebraic Modeling System (GAMS). To represent behavioural response while keeping model run-time in mind all non-linear terms were transformed into linear ones using piece-wise linear approximation (PLA). This resulted in a Mixed Integer Problem (MIP) formulation which is described in chapter 2.4. Subsequently, the deterministic equivalent (DE) of the stochastic MIP is generated via automated reformulation. To have the generated DE be solved with acceptable computational effort it is necessary to restrict the number of scenarios to a modest level. However, this obviously affects the accuracy of the outcome. This is especially the case if several uncertain parameters are used in an equation which has an unknown posterior distribution. Commonly, Monte Carlo simulation can be applied to lessen the number of scenarios. Furthermore, rejection sampling is utilized in the context of this thesis to reduce the number of samples when parameters are not independent. Though a high number of scenarios is generally preferred, reducing it to 20 is considered acceptable to analyse the different scenarios described in chapter 6.2. However, it is advisable to increase the number of scenarios in policy-relevant settings, especially if the focus is on risk aversion and, thus, the tail of the distribution. Due to the comparative nature of the following analysis resampling was avoided.

6.2 Scenario set-up

Two major parameters are selected and it is investigated how their values affect the objective of the optimization problem. Their values are varied to conduct sensitivity analyses and determine their influence on the overall outcome. These parameters are:

1. A predefined **reduction goal** for NO_x emissions: As aforementioned, diesel-fuelled cars and vans emit much higher levels of NO_x under real driving conditions than compared to measurements when on a dynamometer (Carslaw et al., 2011; Franco et al., 2014). This reduction goal defines a constraint to the optimization problem which ensures that NO_x emission from these vehicles are reduced. Reduction goals of 25% and 75% relative to 2030 reference emission levels from Diesel-fuelled vehicles

are assessed within this thesis. A reduction of 75% compared to the reference emissions resembles the case of the affected vehicles complying to a conformity factor (CF) of about 1.5 on average (see chapter 6.3 for details on these assumptions and chapter 3.1 for details on the reference levels). The scenarios will be labelled **NR25** and **NR75**, respectively.

2. The **risk-affinity factor** ϕ : This is the weighting factor between the expected value (EV) term and the conditional value-at-risk (CVaR) term in the objective function, thus balancing risk-neutral and risk-averse stance of a decision-maker. The parameter will be analysed in chapter 6.4 aiming to determine how it affects the model outcome in terms of total net benefit to society and specific policy selection. The scenarios optimized under a risk-neutral objective function will be labelled **NEUT** ($\phi = 1$) and scenarios under risk-averse stance will be labelled **AVRS** ($\phi = 0$). All risk-averse scenarios will be optimized under $\theta = 0.2$, i.e. the CVaR represents the EV within the tail of the distribution representing 20% of the scenarios with worst net benefit (see chapter 2.5 for details). Additionally, $\phi = \frac{1}{3}$ and $\phi = \frac{2}{3}$ will be assessed to analyse the non-linear behaviour of ϕ .

Apart from these parameters the pool of policies to choose from obviously determines the outcome of the optimization as well. It was described in chapter 2.2.2 how the policy selection is handled during this process. In the following the technical options and policies aiming to elicit behavioural changes will be analysed simultaneously.

The list of policies and technical abatement options is given in Tables 6-1 and 6-2, respectively, along with references in this thesis that provide a more detailed description and the geographical scope (i.e. central activity district (CAD), urban or non-urban).

Table 6-1: Summary of policies.

Short name	Geographical scope	Vehicle category	Main intention	Chapter
Increase fuel price	All	All	Push individual travel towards public transport.	4.3.1
Adjust public bus ticket price ^a	Urban	Public buses	Attract individual travellers or travellers from rail-bound alternatives.	4.3.2
Adjust metro/tram ticket price ^a	Urban	Metro/Tram	Attract individual travellers or travellers from on-road public alternatives.	4.3.3
Adjust passenger train ticket price ^a	Urban	Passenger trains	Attract individual travellers or travellers from other public alternatives.	4.3.3
Adjust coach fares	Non-urban	Coaches	Foster modal shift from individual long-distance travel towards coaches.	4.3.6
Adjust long-distance train fares	Non-urban	Long-distance trains	Foster modal shift from individual long-distance travel towards trains.	4.3.5
City toll	CAD	All	Reduce individual travel in central urban areas via distance-based toll up to 0.40 €/PKM.	4.3.4
Scrapping bonus for old vehicles	All ^b	PCs & vans	Incentivise owners of old diesel vehicles to buy replacement fulfilling Euro 6d.	5.2

^a Urban public transport prices may be entangled (see text for details). ^b Mostly focussed on urban areas in which old diesel vehicles are banned via low-emission zones (LEZs).

Table 6-2: Summary of technical abatement options.

Short name	Geographical scope	Vehicle category	Desired effect	Chapter
Software patches for Diesel vehicles	All	PCs & vans	Software updates have shown to reduce NO _x from Euro 5 diesel vehicles.	5.1.1
Retrofit improved SCR system	All	PCs & vans	Tests showed retrofit SCR systems to reduce NO _x emission by up to 95%.	5.1.2
Retrofit improved SCR system	All ^a	Public buses	SCR system manufacturers assume levels of NO _x emission reduction similar to cars.	5.1.2
Retrofit DPF system	All ^b	All	The low remaining share of pre-Euro 4 diesels in the fleet has to retrofit DPFs when not buying a new car instead ^c .	5.3

^a Mostly focussed on urban areas in which old diesel vehicles are banned via LEZs.

^b Mostly focussed on non-urban areas as affected vehicles are likely banned from LEZs anyway.

^c Scrapping bonus provided when buying a new car; see Table 6-1.

6.3 NO_x reduction goals

In the following the effect of different NO_x reduction goals is analysed. These reduction goals determine a specific constraint to the optimization problem: For the problem to solve to optimality it is required that in all scenarios the damages linked to NO_x emissions from diesel-fuelled PCs and vans are reduced by a predefined threshold.

According to [UBA \(2017b\)](#), exhaust NO_x from Euro 4, 5 and 6 diesel PCs exceeds the limit values by 170%, 403% and 534%, respectively. This corresponds to CFs of 2.70, 5.03 and 6.34 for the respective emission standards. To put a 75% reduction goal into perspective: Evenly distributed reductions would result in average CFs of 0.68, 1.26 and 1.59. This corresponds to an overall CF of about 1.5 for the affected vehicles, given the high share of Euro 6 diesels in the 2030 reference fleet (cf. Figure 3-7 in chapter 3).

The most cost-efficient options will be chosen by the solver from policy instruments and technical options to achieve the reduction goal. Technical options for emission reduction are described in chapter 5. There exist mainly two alternative technical options to reduce NO_x emission from the majority of these vehicles, namely software patches and retrofit SCR systems. NO_x reduction goals of 25% (**NR25**) and 75% (**NR75**) relative to 2030 reference emission levels from diesel-fuelled vehicles are assessed within this thesis (see scenario setup described in chapter 6.2). The rationale is to represent the respective removal efficiencies of software patches (at about 20 to 30%) and advanced hardware retrofit options (at up to 90%). It is required that in both urban and non-urban areas these limits have to be met individually. For these two reduction goals the technical options are accompanied by banning old diesel cars from urban areas via LEZs (see chapter 5.2). Another scenario labelled **NOR-NOLEZ** will be assessed in which neither a reduction goal nor a LEZ is enforced but could potentially be chosen during optimization if this decision maximizes social welfare.

In the context of this thesis the following assumptions for ultra-low emission zones (ULEZs) are made: They are established in all urban areas under study and follow along the suggestions of the aforementioned ruling of the Stuttgart administrative court. A detailed description of the assumptions for this measure based on [Verwaltungsgericht Stuttgart \(2017\)](#) is given in chapter 5.2. In summary, the entry to urban areas is not

allowed for petrol-fuelled and gas-powered cars and vans not meeting Euro 3 emission standard along with diesel-fuelled vehicles classified as Euro 5 or lower. As a result, measures need to be taken like software updates (cf. chapter 5.1.1) or even SCR retrofit options (cf. chapter 5.1.2). A more strict variant of this policy is also analysed which forbids entry for diesel-fuelled cars and vans classified as Euro 6 on a dynamometer but do not meet the limit values under real driving emissions (RDE) conditions.

Overall ranges of net benefit for the mentioned scenarios in which both risk-averse (**AVRS**) and risk-neutral (**NEUT**) stance of the decision-maker has been considered are given in Table 6-3. In summary, all of the scenarios show a positive expected net benefit independent of the specific objective or constraints. It is evident that the expected benefit of NR25-NEUT estimated at 84.2 (43.4; 149.2) bn-€ is almost the same as for the social welfare optimum determined under NOR-NOLEZ-NEUT which is estimated at 84.3 (43.5; 149.2) bn-€. If a more stringent reduction goal of 75% is enforced the expected net benefit drops to 79.8 (41.7; 148.9) bn-€.

One can observe from Figure 6-3 that this is mainly a result of higher spendings on technology options to reduce NO_x emissions. The lowest technology cost is found under social-welfare maximization. When comparing the two reduction goals with LEZs in place these spendings increase from 13.2 (10.7; 16.2) bn-€ for at least 25% reduction to 14.6 (12.6; 16.2) bn-€ for a reduction of 75%.

Interestingly, the estimated total avoided damage drops as well from 99.8 (57.8; 165.1) bn-€ to 96.8 (59.8; 165.0) bn-€. This may seem counter-intuitive to more stringent NO_x reduction goals: Intuitively, one might assume that the avoided NO_x emissions from Diesel-fuelled cars should automatically lead to more damage being avoided. Unfortunately, the positive effect is offset by other activities which are not affected by the

Table 6-3: Overall net benefit [bn-€] for given NO_x reduction goals. 90% confidence intervals (CIs) are given in parentheses.

Scenario name	NOR-NOLEZ-...	NR25-...	NR75-...
...-NEUT	84.3 (43.5; 149.2)	84.2 (43.4; 149.2)	79.8 (41.7; 148.9)
...-AVRS	57.7 (44.6; 86.4)	60.2 (44.5; 121.6)	63.4 (42.6; 123.5)



Figure 6-1: Technology distribution within fleet of diesel-fuelled cars and vans in urban areas across Europe. The lower two scenarios have LEZs in place. The figure shows technology distribution in the reference case (top), social-welfare optimum (2nd from top), and with NOx reduction goals of 25% (3rd from top) and 75% (bottom) as a result of taking different measures.

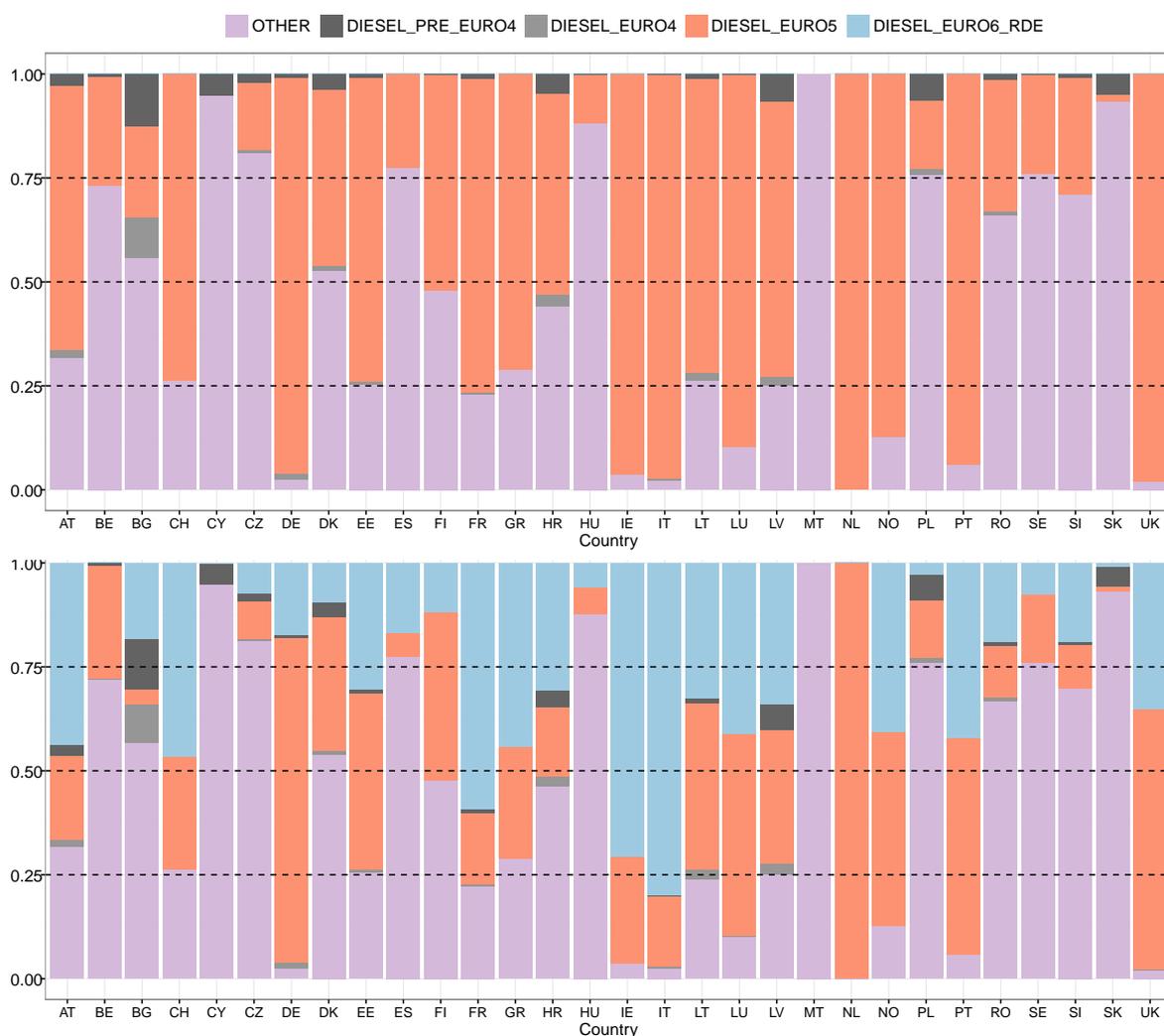


Figure 6-2: Technology distribution within city bus fleet across Europe. Note that public buses are exempt from LEZ regulation and NO_x reduction goals. The figure shows technology distribution in the reference case (top) and with NO_x reduction goals of 75% (bottom) as a result of taking cost-efficient measures. Others are mostly compressed natural gas (CNG) or hybrids.

constraint as the reduction goal only covers a subset of activities, namely Diesel-fuelled passenger cars. This is an interesting result for the following reason: In fact, this is an argument that pollutant-specific policies and reduction goals are irrational but maximization of social welfare as a whole should be addressed. This is in line with the criticism expressed towards single-pollutant IAMs (cf. chapter 1.4). However, the flexible model formulation (cf. chapter 2) allows to assess such goals which enables policy-makers to underpin decisions with quantitative results. This is particularly useful in situations where a small number of options has to be compared. For instance, interests of car vendors and past buyers currently strongly diverge when addressing the question as to whether cheaper software updates or more expensive retrofit options should be considered.

With a more stringent reduction goal in place and with higher adoption rates of technology options diesel PC and van fleet composition changes. The technology distribution in urban areas across Europe is shown in Figure 6-1. The top figure shows the reference distribution and the second row figure shows the outcome under social-welfare optimum (SWO) conditions. Note that these two scenarios do not have LEZs in place and, thus, ordinary Euro 5 vehicles are not banned from urban areas. The lower two figures show technology distribution with NO_x reduction goals of 25% (third from top) and 75% (bottom) and LEZs in place. City buses are exempt from the NO_x regulations. Their technology distribution is shown in Figure 6-2 and will be discussed later.

Varying monetary impact of NO_x emissions, differences in policies and response along with other parameters results in a non-homogeneous replacement of technology across countries. However, under all scenarios a large part of the diesel-fuelled fleet complies to Euro 6 emission standard under RDE. This corresponds to a CF of 1, going beyond current future legislation for Euro 6d-TEMP (CF: 2.1) and Euro 6d (CF: 1.5). These are either retrofits of ordinary Euro 6 cars using BNOx-SCR or newly bought cars as replacements for pre-Euro 6 diesels. Note, that none of the vehicles in the reference case was assumed to comply to these limits. To the contrary, ordinary Euro 6 cars and vans not meeting limit values under RDE conditions were predominant in the reference case comprising 93.8% of the fleet. This is drastically reduced to only one third across Europe in these scenarios (34.3% under NR25, 28.1% under NR75 and 34.3% under NOR-NOLEZ). After policy intervention the share of vehicles complying to Euro 6 limit values

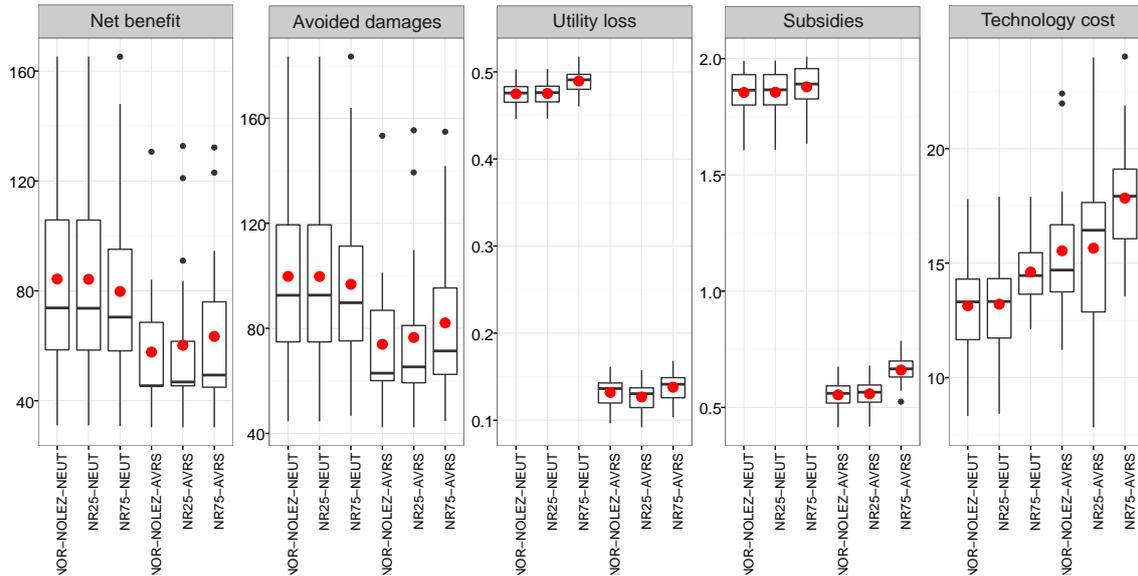


Figure 6-3: Modelled net benefit, avoided damages, utility loss, subsidies and technology cost given for six different NO_x reduction scenarios (x-axis). Values are given in billion €. Box-Whisker plots of show median (bold horizontal line), mean (red dot), middle 50% of the results (box), data points without outliers (vertical lines), and outliers (black dots).

under RDE comprises almost one half of the fleet under moderate intervention (49.6% under NR25 and 49.0% under NOR-NOLEZ). Under stricter regulation it even increases to 57.9% (NR75).

The tighter the NO_x reduction goal the less contribution by Euro 6 cars that received a software update (SWU) to the whole fleet can be observed: Their share drops from 15.4% in each of the two moderate cases to 13.4% under NR75. Again, none of the above technologies was present in the reference case.

Recall that ordinary Euro 5 diesel PCs and vans were deterred from entering a LEZ but exception was made for Euro 5 diesels that received a software update. This is justified as they play only a minor role comprising only about 0.6% of driven person-kilometres (PKMs) under moderate reduction and as little as 0.1% under a more strict goal (NR75).

In the risk-averse case policies are selected and measures taken to reduce overall uncertainty of the net benefit. This can be seen in Figure 6-3: Note the lines – so-called whiskers – spanning vertically from the boxes. The bottom and top line of the box rep-

resent the first and third quartiles where the whiskers start. The thick line inside the box is the median. Avoided damage estimates as well as net benefit estimates under risk-averse scenarios have substantially shorter whiskers. From the above one can conclude that shorter whiskers imply less dispersion in the distribution. Recall that under risk aversion the CVaR is maximized as opposed to the EV in the risk-neutral case. This may come at the cost of lower expected overall net-benefit but yields higher expected benefit in the worst cases. This is clearly linked with the high uncertainty associated with the estimation of behavioural response to policy intervention. The influence of the risk-affinity factor ϕ on policy decisions is discussed in chapter 6.4.

Figure 6-3 also shows a distinction into net benefit, avoided damages, utility losses, induced subsidies and technology costs. It can be observed that technology options are generally favoured over policies eliciting behavioural change under risk aversion. This results in substantially lower utility losses and lower subsidies in AVRS scenarios compared to NEUT scenarios.

6.4 Impact of risk aversion vs. risk neutrality

In this chapter the influence of a decision-maker's attitude towards risk on policy selection is analysed. Recall that the parameter ϕ balances risk-neutrality represented by the EV of the objective function and risk aversion represented by its CVaR. The parameter ϕ can take any value on the interval $[0; 1]$ but is naturally delicate to determine as a person's attitude towards risk is difficult to quantify. Making matters worse the effect of ϕ is

Table 6-4: Overall net benefit in billion Euros for given values of ϕ . 90% CIs are given in parentheses.

Scenario	NOR-NOLEZ-...	NR75-...
...-NEUT	84.3 (43.5; 149.2)	79.8 (41.7; 148.9)
...-: $\phi = \frac{2}{3}$	84.3 (43.8; 149.4)	79.7 (42.0; 149.1)
...-: $\phi = \frac{1}{3}$	84.0 (44.3; 149.7)	79.4 (42.4; 149.3)
...-AVRS	57.8 (44.6; 86.4)	63.4 (42.6; 123.5)

increases.

All outcomes show positive net benefit even at the lower confidence level. In fact, the differences for the lower bound of the 90% CI are very small in relation to the overall outcome. However, in the risk-averse case the expected net benefit is substantially lower at 63.4 bn-€ compared to the neutral case at 79.8 bn-€. As mentioned before, ϕ has highly non-linear impact on the overall net benefit. The model outcomes are differentiated into total net benefit, avoided damages, utility losses, induced subsidies and technology costs as shown in Figure 6-4. A general pattern can be observed: As in the previous analysis, technology options are favoured over policies eliciting behavioural change under risk aversion. With decreasing value of ϕ the impact of policies aiming for behavioural change diminishes. This can be explained by the considerable uncertainty of the underlying meta-regression models which are used to quantify the behavioural response. Obviously, their uncertainty renders overall policy decisions uncertain as well. This results in substantially lower utility losses and lower subsidies in AVRS scenarios compared to NEUT scenarios, implying there is a substantially lower shift from individual traffic to public transportation systems. It is worth investigating in more detail the effect of risk aversion on policy and measure selection. Thus, the effect of ϕ on the implementation rates of the policies shown in Table 6-1 is described in the following.

Different types of road pricing schemes exist. The most prominent ones are introduced in chapter 4.3.4. Consider distance-based tolls which the optimisation approach may choose to implement in CADs as a subregion of urban areas. The impact of this policy instrument is estimated based on the outcomes of one of the meta-regression models developed in chapter 4.3. Recall that these tolls can be placed on top of LEZs meaning that apart from deterring specific vehicles from all urban areas the remaining ones have an additional toll implied on them. In this study, tolls are billed per PKM instead of vehicle-kilometre (VKM) due to model implementation constraints. Consequently, tolls are affected by occupancy rates which are on average higher for vans than for PCs. It is recommended that the suggested values are recalculated based on VKM when used for actual policy use to not put higher occupancy rates at a disadvantage. Figure 6-5 shows optimal distance-based city tolls per country under a 75% NO_x reduction constraint. Recommendations in the risk-neutral case are shaded in blue whereas suggestions under risk-averse stance

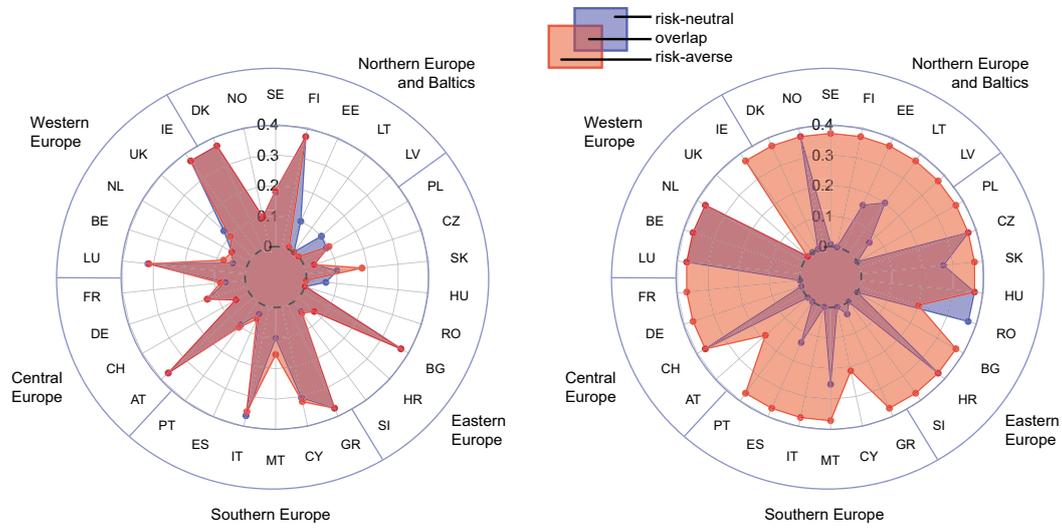


Figure 6-5: Recommended distance-based city toll from 0 to 0.40 Euro/PKM (additional cost) within CADs under NR75. The figure shows respective toll for PCs (left) and vans (right) in the risk-neutral case (NEUT, blue) and the risk-averse case (AVRS, red). Overlap is shown in purple.

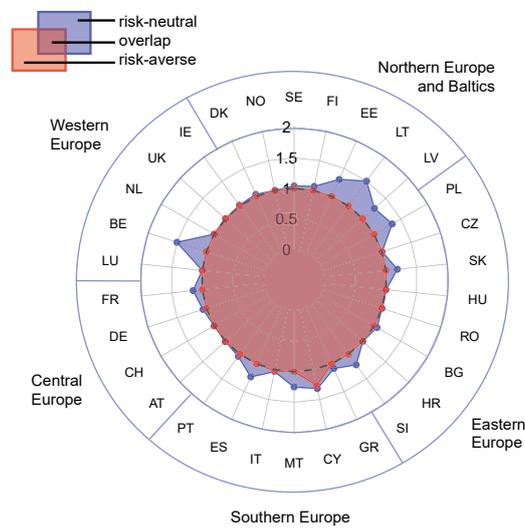


Figure 6-6: Recommended fuel cost adjustment under NR75. The figure shows the respective toll for PCs (left) and vans (right) in the risk-neutral case (NEUT, blue) and the risk-averse case (AVRS, red). Overlap is shown in purple.

are shaded in red. There is no obvious geographical pattern for applying distance-based tolls on PCs across Europe: High tolls are recommended for the Northern countries of Ireland, Denmark and Finland as well as for Mediterranean countries, namely Italy and Greece, but also for Bulgaria, Luxembourg and Austria. These countries differ largely in population density and fleet composition. However, there is striking agreement between the risk-neutral and risk-averse scenario which suggests that city tolls for PCs is a low-risk policy in these areas. Under risk-averse stance city tolls are recommended as an almost universal policy within central urban areas to induce modal shifts from individual travel by vans to public transportation. When a decision-makers risk attitude is neutral other options seem more favourable but there is overlap for some Eastern European countries, the Benelux Union, Norway and Switzerland.

No adjustment of fuel prices can be recommended to a risk-averse decision-maker as is evident from Figure 6-6. Even though the results of numerous studies that assess the connection between fuel price changes and individual travel demand went into the meta-regression model (cf. chapter 4.3), the predicted behavioural change remains considerably uncertain. Cyprus is an exception which can be explained by the limited number of public transport alternatives on the island. The following two initial situations in the reference scenario can to some extent explain the recommendation of increases in fuel tax to induce modal shift under the NEUT scenario: Firstly, high external costs per PKM driven are estimated for the densely-populated urban areas of Belgium. In fact, external costs in Belgium are estimated to be about 30 to 40% higher than in area states like Germany or France. Secondly, the moderate increase of 25 to 50% in the Baltic states, Spain and Slovakia seems justifiable as these countries are projected to have a quite old reference fleet of private vehicles compared to other European countries. This has considerable positive effect on the avoided damages when inducing a modal shift. However, it can be summarized that increasing fuel prices seems to be a high-risk policy in terms of net benefit and that other policies should be considered as well.

In urban areas ticket prices for local public transportation systems usually do not depend on the actual mode taken, i.e. buying a ticket will allow the traveller to use both on-road and rail-bound transportation systems. Accordingly, ticket price adjustments are constrained in the model to be uniform in urban areas independent of the specific mode

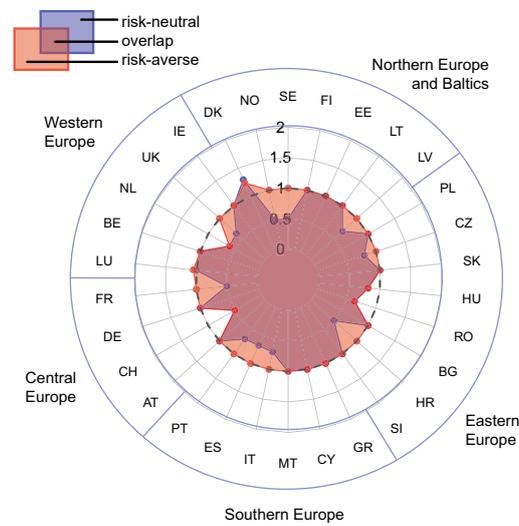


Figure 6-7: Recommended price adjustments for local public transport. Prices of urban trains, metro/tram and public buses are entangled. The figure shows the risk-neutral case (NEUT, blue) and the risk-averse case (AVRS, red). Overlap is shown in purple.

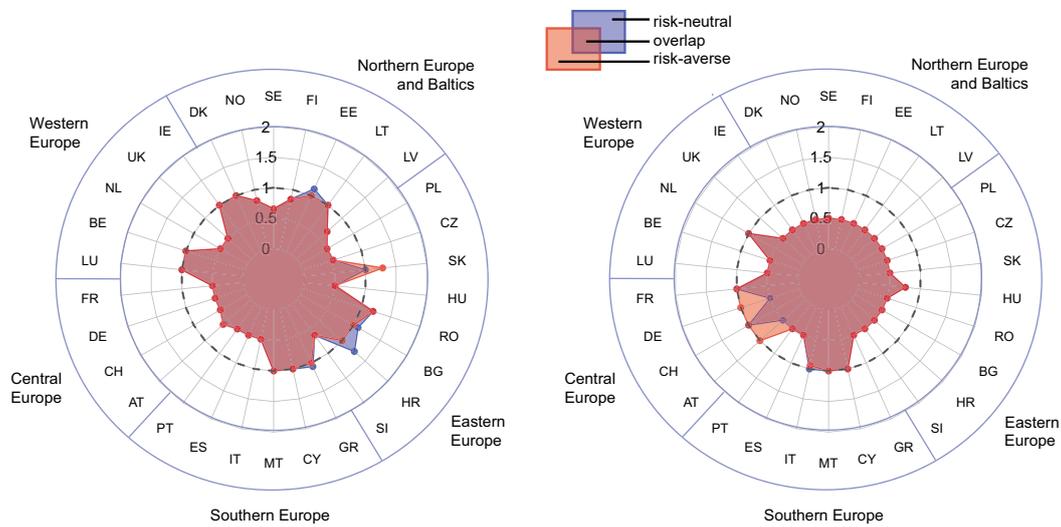


Figure 6-8: Recommended price adjustments for long-distance trains (left) and coaches (right) in the risk-neutral case (NEUT, blue) and the risk-averse case (AVRS, red). Overlap is shown in purple.

of transportation. The respective recommendations for policies affecting ticket prices are given in Figure 6-7.

Urban public transport is traditionally considered the 'green' alternative to individual motorized travel. Hence, it is often recommended to city authorities to extend public transportation infrastructure or improve its service, availability and access to attract individual travellers. Thus, it is not surprising that ticket fares should be either kept constant or should be reduced under risk-neutral stance. However, *prima facie* the recommendation of not reducing ticket prices in a risk-averse scenario appears odd. This is, however, explained by the aforementioned inter-dependencies of policies and measures: A risk-averse decision-maker is endorsed to promote or enforce technology uptake in individual travel to make private transportation more eco-friendly. This is underlined by the substantially higher technology cost for the risk-averse scenario NR75-AVRS compared to scenarios in which $\phi > 0$ (cf. Figure 6-4). It is assumed that public buses are exempt from LEZs and thus their technology uptake is almost independent from the decision-maker's risk-attitude but corresponds to the respective most cost-efficient contribution as shown in Figure 6-2.

Outside of cities public transport considered in this thesis consists of long-distance trains and overland coaches. With the data at hand, massive promotion of non-urban public transport is suggested in many countries to attract individual travellers. This is achieved by extensively lowering ticket prices in many countries. Suggested price adjustments are given in Figure 6-8. There is considerable overlap for recommendations to risk-averse and risk-neutral decision-makers which usually implies that recommended price decreases impose low risk on total net benefit. However, it should be noted that the respective cross-elasticity estimates suffer from lack of data to support the development of meta-regression models which led to a broader estimate as already mentioned in chapter 4.3. For instance, the available studies concluded that change in car travel demand with respect to lowering train ticket prices is very low. However, the supporting studies were conducted in the United States and Australia and are, thus, difficult to transfer into the European context as car ownership has a rather different relative importance in these countries compared to most of the European countries. While this was acknowledged in the estimates it seems surprising that such drastic reduction in non-urban public transport

is suggested. Nevertheless, it as been shown in chapter 4.3 that meta-regression models can be developed when more data becomes available.

7 Conclusions and outlook

This chapter concludes this thesis: The presented work is summarized in light of contributing to the achievement of the main objectives. This is presented in chapter 7.1. Furthermore, the limitations of the approach with respect to uncertainty treatment are discussed within a critical appraisal in chapter 7.2. Finally, an outlook on four potential future research directions is given in chapter 7.3.

7.1 Revisiting the objectives

The contributions of this thesis are a consequence of the two major objectives outlined in chapter 1.2. In the following, the individual contributions to these objectives are summarized.

The first objective (**O1**) of this thesis aimed to enable decision-makers to determine cost-efficient environmental protection strategies under different levels of risk aversion. The problem was addressed by developing a consistent mathematical modelling framework and by formulating a stochastic optimization approach as described in chapter 2. To represent different levels of risk aversion in the objective function a single parameter ϕ was introduced in chapter 2.5. It can be summarized that the first objective is met when a decision-maker conducts a sensitivity analysis of ϕ to determine its impact on policy selection. Such analysis was conducted within the scope of a case study in chapter 6.4.

Contributions to the second objective (**O2**) of this work intended to enable decision-makers to conduct assessments of a conjoint application of both technical options and policies inducing behavioural change. While the former is possible with other integrated assessment modelling (IAM) frameworks, too, the latter is addressed using a novel approach developed in the scope of this thesis: The impact of non-technical measures was quantified in chapter 4 by conducting a meta-regression analysis (MRA) on a vast body of literature on transport demand elasticities in conjunction with public statistics. Subsequently, parsimonious meta-regression models were developed whose outcomes can be easily analysed due to their low number of parameters. To cope with the non-linearity in

behavioural response a piece-wise linear approximation (PLA) approach was developed in chapter 2.4. Conjoint application of measures is formalized in chapter 2. Within the aforementioned case study, technical options and non-technical measures are assessed simultaneously and the results are presented in chapter 6.

7.2 Limitations of the approach with respect to treatment of uncertainty

[Anenberg et al. \(2016\)](#) survey several recent assessment tools of ambient air pollution health risk with respect to their treatment of uncertainty. The authors summarize that none of them is capable of properly addressing all uncertainties.

This work deals extensively with the assessment and integration of uncertainty in the context of the presented optimization approach. However, there are obviously limitations with respect to the extent proper treatment can be achieved. To point out these limitations and potential ways to overcome them, different forms and sources of uncertainty have to be addressed as follows.

Commonly, uncertainty is categorized into two types referring to the nature of uncertainty, namely epistemic uncertainty and aleatory uncertainty: Aleatory uncertainty is statistical uncertainty which occurs due to inherent variability or general randomness. The observed randomness is due to natural process of what is observed. It is, thus, irreducible from a modelling perspective and is commonly characterized by a probability distribution.. Epistemic uncertainty is systematic uncertainty which occurs due to limited knowledge about a modelled or actual system, e.g. when a parameter value could be known in theory but is not in practice. The advantage of parameters falling into this category is that epistemic uncertainty can be reduced. Often, historical data is analysed to understand underlying processes to reduce the gaps in knowledge. To show how epistemic uncertainty could be reduced in the context of this thesis, a further distinction of uncertainty focusing on the sources of uncertainty is discussed in the following.

The following types of uncertainty are discussed: Parameter uncertainty, experimental uncertainty, interpolation uncertainty, structural uncertainty and numerical or algorithm-

mic uncertainty. The rationale is that levels of uncertainty differ across the sources and that when dealing with uncertainty that may be overcome or reduced – epistemic uncertainty according to above categorization – the strategies to do so may differ considerably.

Parameter uncertainty and variability refers to uncertain input to mathematical models whose exact values cannot be determined precisely using statistical methods and cannot be controlled in experiments. One may argue that all input parameters discussed in chapter 3 fall under this category of uncertainty, for instance emission factors or dose-response relationships. However, these model parameters are usually derived from observations, measurements and experiments, e.g. dose-response functions are determined by long-term epidemiological studies. Thus, these parameters show inherent experimental uncertainty. Experimental uncertainty is generally concerned with observation error and the variability of measurements. Another prominent example may be emission factors which are derived from measurements, e.g. the NO_x content in exhaust gas. One may argue that experimental uncertainty is simply an agglomeration of other sources of uncertainty that may occur during experiments, especially when experiments are used to observe natural processes which are inherently uncertain. Obviously, experimental uncertainty is inevitable. Commonly, an approach to reduce experimental uncertainty is the repetition of experiments. Other approaches like data fusion exist which aim to reduce uncertainty of parameters from multiple measurements which may have been collected during dissimilar experiments. A common example is to use data fusion to reduce the uncertainty of ambient air quality estimates by fusing data from ground-based measuring stations with satellite-based measurements, e.g. using linear quadratic estimation referred to as Kalman filter. In the context of technical options, investment cost and operational cost are determined based on a number of parameters whose uncertainty ranges are given in chapter 5. However, the lifetime n of a measure and the interest rate r have considerable effect on the annuity estimate and one may consider conducting a sensitivity analysis of these parameters to determine their effect on the cost-effectiveness of a technical option. A consistent methodology to derive meta-regression models from literature on transport elasticities has been presented. Nevertheless, it is of paramount importance to reduce the huge parameter uncertainty in this context to make policy recommendations more useful (cf. chapter 6).

In general, source-specific uncertainty in estimations derived by applying the Impact Pathway Approach (IPA) is sometimes difficult to categorize due to the propagation of uncertainty along the assessment chain. For instance, the estimation of future air quality levels using computer models is affected by many sources of uncertainty which are at least but not limited to: (i) structural uncertainty of individual atmospheric models due to different formulations of chemical and physical processes, (ii) their respective input parameter uncertainty like future meteorological conditions. One may even argue that future meteorological conditions are likely subject to aleatory uncertainty. Furthermore, future economic conditions which influences activities and emission levels are uncertain. In this thesis, considerable effort went into reduction of uncertainty of future air quality level estimates (cf. chapter 3.3).

Additionally, when assessing policies in an optimization context, it is argued in this thesis that parametrized atmospheric models need to be used due to limited computational resources which introduced additional interpolation uncertainty. Interpolation uncertainty also occurs due to piece-wise linearisation of non-linear terms. Approaches were presented that are capable of reducing interpolation uncertainty by determining the optimal λ -values for given settings. Sensitivity analysis can also be recommended to find adequate values for λ (cf. chapter 2.4).

Structural uncertainty refers to general model or methodological inadequacy which for obvious reasons is difficult to assess. One can safely argue that the concept of cross-elasticities is well-established in economics as is the concept of consumer surplus and utility losses. Also, the determination of external impacts using the IPA has proven useful in the context of cost-benefit analysis (CBA) in environmental economics and the standard-price approach is accepted to estimate climate impacts. However, the latter is related to outcomes of political debate in climate mitigation goals and thus had to be associated with large uncertainties (cf. chapter 3.5). With respect to structural uncertainty of the stochastic optimization approach, one can argue that the sample size is likely to have impact on the uncertainty of the results. However, this can be overcome by choosing a bigger sample size or sample according to specific sampling approaches (e.g. importance sampling or rejection sampling). Spatial granularity of all parameters was also chosen to account for data availability and reasonable model size. However, the

effect of a different granularity on the model outcome is difficult to assess.

Numerical or algorithmic uncertainty can safely be considered low in the context of this work. Numeric uncertainty occurs, for instance, when approximating integrals as is done for the estimation of utility losses in chapter 2. Again, this is adjustable by choosing proper values of λ and increasing the sample size. Also, using sensitivity analysis it is possible to give upper and lower bounds for the approximation of consumer surplus by applying the rule of a half (RoH).

7.3 Future research directions

One can foresee several future research directions based on the model proposed and presented in this work. Four quite different directions that are considered the most relevant ones are discussed in the following:

1. It is safe to argue that the robustness of policy recommendations can be improved by collecting specific data, especially transport demand elasticities to better quantify the effects of non-technical measures. Parameter uncertainty with respect to the modelling framework is, thus, separately discussed in the previous chapter. Nevertheless, data collection and application of uncertainty reduction approaches like data fusion could be further examined and applied.
2. It is worthwhile to further investigate the effect of risk aversion (i.e. parameter ϕ) on policy selection. Such analysis was conducted in chapter 6 in the context of the case study. Not surprisingly, it can be concluded that the effect of ϕ on policy selection is quite erratic. Obviously, policy selection for varying values of ϕ is difficult to predict as the impact determination is non-linear when non-technical measures are involved. After the sets of policies and measures were defined, decision-makers are well-advised to conduct proper sensitivity analysis of ϕ .
3. Policy-making in the field of environmental protection is often more concerned about meeting limit values with respect to concentration levels at measuring station as opposed to finding a solution that maximizes social welfare. As a consequence, policies sometimes have to specifically target the reduction of these levels. Some

minor adjustments to the model need to be made to deal with this issue: First, the source-receptor relationships used to determine the environmental impacts should not be collapsed into the damage estimation but the estimated concentration level should be kept separately during optimization (cf. eq. (2-14) in chapter 2.2.3). This can then easily be combined with the projected air quality levels as determined in chapter 3.3.1. Finally, the objective function and the model constraints have to reflect the goal of meeting limit values: A simple approach would include financial penalties for violations which has the advantage of not having to adjust the objective function. The obvious drawback is the difficulty of determining proper values for such penalties. A more sophisticated approach involves the utilization of chance constraints or percentile optimization and is only briefly sketched here. Chance constraints, as opposed to regular strict constraints, ensure that a constraint is met with at least a predefined probability only and thus may be violated in some scenarios. This leverage gives more flexibility to the optimization approach in selecting policies towards the fulfilment of the objective function. Percentile optimization would, in fact, enable the decision-maker to put more emphasis on fulfilling the limit values by adjusting the objective function in such a way that the probability of violating the constraints is minimized.

4. Successful policy making should be concerned with perceived justice of policies in the general public. The Kaldor-Hicks criterion of welfare economics postulates compensation to account for imbalances during maximization of the net benefit for society. However, while cost-efficiency of policies is important, the public's acceptance of measures should be estimated and considered as well: Low acceptance is an obstacle for policy implementation ([Schade and Schlag, 2003b](#); [Eriksson et al., 2008](#)). In general, it is difficult to persuade people to make sacrifices now for the sake of a long-term pay-off, especially when being uncertain about the outcome. Also, they might experience the costs and utility losses but might not necessarily be affected by the benefits. The benefits might even only happen in the future whereas the costs might be implied on the individuals in the present. When following the terminology of [Schade and Schlag \(2003a\)](#), acceptability refers to someone's attitude towards a policy measure to be introduced in the future, while acceptance includes respondents' behavioural reactions as expression of their attitude after the

introduction of a measure. Thus, perceived injustice may lead to lower acceptance rate of governmental intervention. It was shown that, due to several circumstances like vehicle age distribution and limited disposable income, the poor are likely more affected by the policies analysed in this thesis (cf. 3.1.2, chapters 3.1.3 and 4.4). As aforementioned in the context of environmental economics an efficient solution may lead to compensation payments. The framework developed in this thesis can be used to support the determination and analysis of such compensation schemes.

A Appendix

A.1 Model input disaggregation

Due to the stochastic nature of the approach the model size depends on both number of scenarios simultaneously under optimization and the level of detail with respect to the representation. Consequently, the model formulation has to balance the two as both introduce uncertainty. The disaggregation levels for the relevant model parameters are given.

With respect to spatial representation each of the 30 considered countries is represented by 3 regions (see Tables A-1 and A-3). Furthermore, 2 periods of the day are considered (see Table A-2). 11 vehicle categories are currently implemented of which 6 are relevant for the scope of this thesis (see Table A-5). The technologies are determined by the reference case and the options analysed in the scope of this thesis (cf. chapter 5, see Table A-6).

Table A-1: Model input disaggregation for regions (R).

Value	Description
CAD	The CAD of a city is its activity centre for a mixed-use area. The central business district covers a similar area. However, the focus of the former is not solely on commercial functions.
URBAN	All urban areas but the CADs.
NONURBAN	Remaining regions that are not considered urban.

Table A-2: Model input disaggregation for periods of the day (PD).

Value	Description
PEAK	Peak (rush) hours of traffic, usually 6-10 am and 4-8 pm.
OFFPEAK	Remaining hours of the day.

Table A-3: Model input disaggregation for countries (*C*) of the European Union, Norway and Switzerland (EU28+2) follows along ISO 3166-1 codes (UK used instead of GB).

Value	Description
AT	Austria
BE	Belgium
BG	Bulgaria
CH	Switzerland
CY	Cyprus
CZ	Czech Republic
DE	Germany
DK	Denmark
EE	Estonia
ES	Spain
FI	Finland
FR	France
GR	Greece
HR	Croatia
HU	Hungary
IE	Ireland
IT	Italy
LT	Lithuania
LU	Luxembourg
LV	Latvia
MT	Malta
NL	Netherlands
NO	Norway
PL	Poland
PT	Portugal
RO	Romania
SE	Sweden
SI	Slovenia
SK	Slovakia
UK	United Kingdom of Great Britain and Northern Ireland

Table A-4: Model input disaggregation for income (I) as proxy for socio-economic status.

Value	Description
Q1	Lowest income quintile.
Q2	Second to lowest income quintile.
Q3	Middle income quintile.
Q4	Second to highest income quintile.
Q5	Highest income quintile.

Table A-5: Model input disaggregation for vehicle category (K).

Value	Description
WALK_CYCLE	Walking or cycling. This is not causing any relevant emissions.
CAR	Passenger cars (incl. sedans, station wagons and hatchbacks).
VAN	Vans are high-roof vehicles with higher average occupancy rates than ordinary passenger cars but also higher fuel use.
MOTORCYCLE	Two- or three-wheeled motor vehicles.
BUS	City buses and coaches, depending on the region (see Table A-1).
TRAIN_PASSGR	Passenger trains, includes long-distance trains (regional trains, inter-city trains and high-speed rail) in non-urban areas as well as commuter trains, rapid trains and tram within cities. Thus, depending on the region (see Table A-1).
TRAIN_FREIGHT	Freight trains. Implemented but not considered in the context of this thesis.
LDT	Light-duty trucks. Implemented but not considered in the context of this thesis.
HDT	Heavy-duty trucks. Implemented but not considered in the context of this thesis.
SHIP_INLAND	Inland ships. Implemented but not considered in the context of this thesis.
AIRCRAFT	Aircraft. Implemented but not considered in the context of this thesis.

Table A-6: Model input disaggregation for technology and fuel (*T*).

Value	Description
NONE	Walking etc.
ELECTRIC	Electronically powered road and rail vehicles. Usually, non-exhaust and life-cycle emissions only.
DIESEL_PRE_EURO4	Diesel-fuelled vehicles not meeting Euro 4/IV.
DIESEL_PRE_EURO4_DPF	DIESEL_PRE_EURO4 with retrofit particle filter (cf. chapter 5.3).
DIESEL_PRE_EURO4_SCR	DIESEL_PRE_EURO4 with retrofit selective catalytic reduction system (cf. chapter 5.1).
DIESEL_EURO4	Diesel-fuelled vehicles meeting Euro 4/IV.
DIESEL_EURO5	Diesel-fuelled vehicles meeting Euro 5/V (NEDC).
DIESEL_EURO5_SWU	Diesel-fuelled vehicles with software update applied. Previously met Euro 5/V (NEDC).
DIESEL_EURO6	Diesel-fuelled vehicles meeting Euro 6/VI (NEDC).
DIESEL_EURO6_SWU	Diesel-fuelled vehicles with software update applied. Previously met Euro 6/VI emission standard (NEDC).
DIESEL_EURO6_RDE	Diesel-fuelled vehicles that meet Euro 6/VI under real driving conditions.
GASOLINE_PRE_EURO4	Gasoline-fuelled vehicles not meeting Euro 4/IV.
GASOLINE_EURO4	Diesel-fuelled vehicles meeting Euro 4/IV.
GASOLINE_EURO5+	Diesel-fuelled vehicles meeting Euro 5/V or 6/VI. Limits similar, particle number not considered.
CNG_PRE_EURO4	CNG-fuelled vehicles not meeting Euro 4/IV.
CNG_EURO4	CNG-fuelled vehicles meeting Euro 4/IV.
CNG_EURO5+	CNG-fuelled vehicles meeting Euro 5/V or 6/VI.
LPG_PRE_EURO4	LPG-fuelled vehicles not meeting Euro 4/IV.
LPG_EURO4	LPG-fuelled vehicles meeting Euro 4/IV.
LPG_EURO5+	LPG-fuelled vehicles meeting Euro 5/V or 6/VI.
RAIL_DIESEL	Diesel-fuelled rail-bound vehicles.
SHIP_MDO	Marine diesel oil; blend of gasoil and heavy fuel oil). Implemented but not considered in this study.
KEROSENE	Kerosene for aircraft. Implemented but not considered in this study.

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Content

Recurrent violation of air quality standards detected at measuring stations worries city authorities across Europe. Accompanied by the recent disclosure of large-scale irregularities in real driving vehicle emissions air pollution control has nowadays taken on greater significance than ever before. Decision-makers aim to reduce the amount adverse effects of polluted air and climate change simultaneously by implementing proper legislation. However, they face severe uncertainties when estimating both people's response to policies and the resulting environmental impact. Obviously, this imposes risk on achieving the desired effect. Furthermore, failure to succeed in reducing the adverse impacts lowers acceptance of policies among the general public.

Recent studies in this field do not sufficiently account for this risk and ignore a decision-maker's level of risk-aversion when recommending policies: While some of the studies acknowledge the existence of large uncertainties in impact estimation, they do not adequately incorporate current knowledge in the analysis. Some studies use expected values only during the optimization approach which leads to results that cannot be considered recommendations for risk-averse decision-makers. Other approaches deliberately overestimate costs in the presence of uncertainty and even exclude uncertain aspects of the assessment entirely from the analysis.

A stochastic optimization approach to determine cost-efficient environmental protection strategies via cost-benefit analysis (CBA) is developed in this thesis. Furthermore, it is integrated into a novel modelling framework that incorporates uncertainty of environmental impacts as well as uncertainty of people's response to policy in a consistent manner. Policy intervention is modelled via implementation of both technical and non-technical measures. A case study is conducted, and its results are presented and discussed. It investigates how further improvements can be achieved in the passenger transport sector of the 28 EU member states plus Norway and Switzerland.