Economic Policy Appraisal and Heterogeneous Users

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Abstract

English

At the beginning of the 21st century, many countries are experiencing major changes in commodity flows and in people's mobility. On the one hand, a globalized world is evolving where division of labor and new markets lead to a strong increase in freight transport. On the other hand, people's mobility patterns are shifting: more leisure related travel in the industrialized countries, more demand for motorized transport in the developing countries. This is expected to lead to an increase of transport-related negative externalities such as congestion, local pollution, and climate change. For this reason, all nations face major challenges in the field of transport infrastructure and policy planning: Political interventions need to be developed which—in addition to technological and regulatory measures—aim for behavioral changes of people. Against this background, the thesis concerns possible improvements in applied Benefit-Cost Analysis (BCA) that can be obtained when introducing heterogeneous user preferences and user attributes into the behavioral model of an agent-based transport simulation. The thesis focuses on the valuation of positive and negative effects for society that might be caused by policy interventions. Several hypothetic policies are introduced in different real-world scenarios, and changes in mobility patterns, changes in exhaust emissions, and changes in well-being are calculated for every individual of the population. In total, three work packages are treated:

1. Analysis of public acceptance problems of transport policies that increase overall welfare for society.

2. Development of a model to forecast the aggregated and spatially disaggregated changes of vehicle-specific warm and cold start emissions.

3. Internalization of vehicle-specific, time-dependent emission costs by a first-best air pollution toll.

The first work package claims that, in practice, a single figure—such as Benefit-Cost Ratio (BCR)—has a strong impact when deciding about transport policies; however, this figure omits implicit distributional effects that emerge on geo-spatial or inter-personal levels. To correct for this, empirically determined, heterogeneous costs preferences of users are introduced into the behavioral model of the transport simulation. This is found to improve the accuracy and forecast ability of the model. Furthermore, the resulting individual utility differences are found to be robust figures for the identification of winners and losers of the policy. For economic analysis, two aggregation and monetization procedures are performed and compared: the time equivalent and the income equivalent approach. Following the income equivalent approach, the results indicate that road user pricing schemes, but also non-monetary policies that aim at shortening travel times, can have regressive impacts on the welfare distribution of society. A progressive (income) tax to finance the measure might therefore not be re-distributive, but might only reflect the individual willingness-to-pay for improving the corresponding services. Finally, the comparison of the two approaches proves to help identifying possible reasons for public refusal of transport policies that are—according to standard BCA—economically beneficial.

The second work package proves the technical feasibility of including heterogeneous user attributes—namely vehicle attributes—into the agent-based transport simulation. A novel Emission Modeling Tool (EMT) is developed to account for detailed air pollution and climate change externalities. Highly differentiated warm and cold start emissions that depend on vehicle types, traffic states, and activity durations are calculated for several hypothetical price changes in car user costs. Aggregated price elasticities of emissions are found to be higher than those of demand. That is, the model is found to capture the positive effects of congestion relief on emission levels. However, a spatially disaggregated analysis shows for high-speed arterials and tangential motorways that average emissions per vehicle kilometer *rise*. This decreases the efficiency of the system in terms of emissions per vehicle kilometer. In contrast, average emissions per vehicle kilometer *drop* in urban areas. This increases the efficiency of the system in terms of emissions per

vehicle kilometer. Even though the latter effect is dominating the first, the results indicate that the EMT captures the effect of an emission optimal speed around 60 km/h which is also found in reality.

The last work package aims at improving decision support in the BCA framework by calculating first-best air pollution tolls. It builds up on the output of the EMT developed in work package two. A novel approach is presented to calculate vehicle-specific, time-dependent air pollution tolls. Comparing this internalization policy to a regulatory measure—a speed limitation to 30 km/h in the inner city—shows that the latter policy is considerably less successful in terms of total emission reduction. It even yields higher inefficiencies than a 'do-nothing' strategy. That means generalized prices beyond the economic optimum for urban travelers and generalized prices below the economic optimum for commuters and freight traffic. Importantly, it is found that the air pollution toll implicitly reduces congestion and therefore works as a congestion pricing scheme. Even though the first-best toll is a rather theoretical concept, the approach proves to help designing transport policies that aim at reducing air pollution in metropolitan areas.

In summary, this thesis highlights several structural issues in the context of current quantitative economic policy appraisal. By means of several Case Studies, it shows how advances in multi-agent transport models could provide valuable additional information for decision makers as well as for public participation processes. The introduction of heterogeneous user preferences and user attributes may capture people's behavior more accurately; however, the thesis concludes that the question on how to weigh gains and losses of different individuals against each other remains a normative one, which has to be solved in socio-political discussions.

Deutsch

Am Anfang des 21. Jahrhunderts sind in vielen Ländern starke Veränderungen in Warenflüssen und im Mobilitätsverhalten von Personen spürbar. Auf der einen Seite entwickelt sich eine globalisierte Welt, in der Arbeitsteilung und die Erschließung neuer Märkte den Warentransport massiv ansteigen lassen. Auf der anderen Seite verändert sich das Mobilitätsverhalten der Menschen: mehr Freizeitverkehr in den Industrieländern, mehr Nachfrage nach motorisiertem Verkehr in Entwicklungs- und Schwellenländern. Es wird erwartet, dass diese Entwicklung zu einem Anstieg der verkehrsbezo-

genen negativen Externalitäten führen wird, wie z.B. Stauerscheinungen, lokale Luftverschmutzung und Klimawandel. Aus diesem Grund sehen sich alle Nationen großen Herausvorderungen im Bereich der Verkehrs- und Infrastrukturplanung gegenüber. Es wird nötig sein – neben technischen und regulativen Interventionen – weitere politische Maßnahmen zu entwickeln, welche auf Verhaltensänderungen der Bürger abzielen. Vor diesem Hintergrund beschäftigt sich diese Arbeit mit möglichen Verbesserungen einer angewandten Nutzen-Kosten-Analyse (NKA), die sich durch die Berücksichtigung von heterogenen Nutzerpräferenzen und Nutzerattributen im Verhaltensmodell einer agentenbasierten Verkehrssimulation ergeben können. Die Arbeit beschäftigt sich mit der Bewertung positiver und negativer Wirkungen auf die Gesellschaft, die sich aufgrund von politischen Maßnahmen ergeben könnten. Dafür werden mehrere hypothetische Maßnahmen in verschiedenen realen Szenarien eingeführt und Änderungen im Mobilitätsverhalten, Änderungen in Abgasemissionen und Änderungen im individuellen Wohlfahrtsniveau werden berechnet. Insgesamt werden drei Arbeitspakete bearbeitet:

1. Analyse von Maßnahmen, welche die gesamtgesellschaftliche Wohlfahrt steigern, in Bezug auf Akzeptanzproblemene.

2. Entwicklung eines Modells zur Vorhersage von aggregierten und räumlich disaggregierten Änderungen fahrzeugspezifischer Warm- und Kaltstartemissionen.

3. Internalisierung von fahrzeugspezifischen, zeitabhängigen Emissionskosten mit Hilfe einer optimalen Luftschadstoffmaut.

Das erste Arbeitspaket geht davon aus, dass in der Praxis einzelne Kennzahlen (wie z.B. das Nutzen-Kosten-Verhältnis) einen starken Einfluss auf die Bewertung von Verkehrsmaßnahmen haben; diese Zahl vernachlässigt allerdings Verteilungseffekte, die auf räumlich differenzierter oder personenspezifischer Ebene implizit entstehen. Um diesem Effekt entgegenzuwirken, werden empirisch bestimmte, heterogene Kostenpräferenzen der Nutzer in das Verhaltensmodell der Verkehrssimulation eingeführt. Zunächst verbessert dies die Genauigkeit und die Vorhersagekraft des Modells. Außerdem zeigt sich, dass die sich ergebenden individuellen Nutzenveränderungen ein robuster Indikator für die Identifizierung von Gewinnern und Verlierern einer Maßnahme darstellt. In der ökonomischen Analyse werden dann zwei Aggregations- und Monetarisierungsmöglichkeiten durchgeführt und

verglichen: der Ansatz über Zeitäquivalente und der Ansatz über Einkommensäquivalente. Für den Ansatz über Einkommensäquivalente deuten die Ergebnisse darauf hin, dass sowohl Maut als auch nicht-monetäre Maßnahmen, die eine Verkürzung der Reisezeiten zum Ziel haben, eine regressive Wirkung auf die Wohlfahrtsverteilung in der Gesellschaft haben können. Eine progressive (Einkommens)steuer zur Finanzierung der Maßnahme könnte aus diesem Grund u.U. nicht umverteilend wirken, da sie lediglich die individuellen Zahlungsbereitschaften zur Verbesserung des Services reflektiert. Zusammenfassend kann gesagt werden, dass der Vergleich der beiden Ansätze es ermöglicht, Gründe für öffentlichen Widerstand zu identifizieren, der sich gegen Projekte wendet, die aus Sicht des üblichen NKA-Ansatzes ökonomisch sinnvoll erscheinen.

Das zweite Arbeitspaket zeigt die technische Möglichkeit, heterogene Nutzerattribute – hier Fahrzeugattribute – in eine agentenbasierte Verkehrssimulation einzubeziehen. Ein neuartiges Emissionsberechnungstool (EMT) wird entwickelt, das detaillierte Luftschadstoff- und Klimawandelexternalitäten berücksichtigt. Hochdifferenzierte Warm- und Kaltstartemissionen, die von Fahrzeugtyp, Verkehrszustand und Aktivitätendauer abhängen, werden im Rahmen mehrerer hypothetischer Erhöhungen der distanzabhängigen Autonutzerkosten berechnet. Es zeigt sich, dass die Preiselastizitäten der Emissionen höher sind als die der Verkehrsnachfrage. Dies bedeutet, dass das Modell in der Lage ist die positiven Effekte von Stauauflösung auf das Emissionsniveau zu beschreiben. Eine räumlich hoch aufgelöste Analyse zeigt allerdings, dass die Emissionen pro Fahrzeugkilometer auf Hauptverkehrsstraßen und tangentialen Autobahnen *ansteigen*. Dies verringert die Effizienz des Systems in Bezug auf die Emissionen pro Fahrzeugkilometer. Auf urbanen Straßen *sinken* diese spezifischen Emissionen hingegen. Dies erhöht die Effizienz des Systems diesbezüglich. Obwohl letzterer Effekt ersteren dominiert zeigt dies, dass das EMT den Effekt einer emissionsoptimalen Geschwindigkeit um 60 km/h widerspiegelt, welcher auch in Realität auftritt.

Das letzte Arbeitspaket zielt darauf ab die Entscheidungsfindung innerhalb einer NKA zu verbessern indem eine optimale Luftschadstoff-Maut berechnet wird. Dazu wird die Ausgabe des EMT verwendet, welches im zweiten Arbeitspaket entwickelt wurde. Es wird ein neuartiger Ansatz vorgestellt, mit dem eine fahrzeugspezifische, zeitabhängige Luftschadstoff-Maut berechnet werden kann. Ein Vergleich dieser Internalisierungsstrategie zu den Wirkungen einer regulativen Maßnahme – eine Reduktion der Höchstge-

schwindigkeit in der Innenstadt auf 30 km/h – zeigt, dass letztere Maßnahme deutlich weniger zur Reduzierung der Gesamtemissionen beiträgt. Die regulative Maßnahme führt sogar zu höheren Ineffizienzen als der Bezugsfall: dies impliziert generalisierte Preise oberhalb des ökonomischen Optimums für Stadtbewohner und generalisierte Preise unterhalb des ökonomischen Optimums für Pendler und Güterverkehr. Die Resultate zeigen auch, dass die Luftschadstoff-Maut auch Zeitverluste reduziert und somit implizit eine Staubepreisung darstellt. Auch wenn eine optimale Maut tendenziell eher ein theoretisches Konstrukt ist, kann gezeigt werden, dass der verwendete Ansatz dafür geeignet ist, Verkehrsmaßnahmen zu bewerten, die auf eine Reduktion von Luftschadstoffemissionen in Metropolregionen abzielen.

Zusammenfassend kann gesagt werden, dass diese Arbeit mehrere strukturelle Probleme im Bereich der aktuellen quantitativen Bewertung von Verkehrsmaßnahmen herausarbeitet. Anhand verschiedener Fallbeispiele wird gezeigt, wie durch Fortschritte in agentenbasierten Verkehrssimulationen wertvolle zusätzliche Informationen sowohl für Entscheidungsträger als auch für öffentliche Beteiligungsverfahren bereitgestellt werden können. Die Einführung heterogener Nutzerpräferenzen und Nutzerattribute beschreibt zwar vermutlich reales Verhalten präziser; abschließend kommt die Arbeit allerdings zu dem Schluss, dass die Frage wie Gewinne und Verluste verschiedener Individuen gegeneinander aufgewogen werden normativ festgelegt werden muss, möglichst im Rahmen gesellschaftspolitischer Diskussionen.

Chapter 1

Introduction

1.1 Motivation

This thesis concerns the identification of improvements in applied Benefit-Cost Analysis (BCA) that can be obtained when introducing heterogeneous user preferences and user attributes into an agent-based transport simulation. For that purpose, several hypothetic policy measures are introduced in different real-world scenarios, and changes in mobility patterns, exhaust emissions, and well-being of individuals are calculated. The thesis focuses on the valuation of positive and negative effects of mobility behavior for society. Hence, the role of project implementation and maintenance costs is not treated. The *exact figures* presented in the Case Studies are not meant to be definitive, fully realistic, or imply any suggestions for policy makers. The ultimate goal is rather to point out *structural issues* in the area of quantitative economic policy appraisal, which operates in the case of transport at the edge between the delicate task of behavioral modeling and the even more delicate task of assigning monetary values to human behavior.

1.1.1 Decision Criteria

Economists have argued that a policy should be initiated and accepted if all individuals of society are expected to feel better off afterwards. Likewise, if all individuals are expected to feel worse off after the change, the policy should not be pursued. However, if the policy is likely to affect some individuals positively and others negatively, the decision whether to accept the policy or not is not as straightforward any more: gains and losses of

different people need to be weighed against each other (see, e.g., Stiglitz, 1983). Moreover, a policy often affects a single individual in several ways which might reinforce, compensate, or over-compensate each other. The net effect on individual utility level can in many situations only be perceived by the individual itself. By applying microeconomic theory to that problem, one might be capable to identify winners and losers of a policy change. However, a comparison of utility changes between individuals will require normative decisions (Ahlheim and Rose, 1989).

1.1.2 Decision Support

Economic policy appraisal comprises in many industrialized countries on national, regional, and urban levels a method called BCA (Mackie and Worlsley, 2013). It is today recognized as the major appraisal technique for public investments (OECD, 2006). The basic idea behind this quantitative method is that one compares the aggregated (discounted) benefits of a measure to the total (discounted) costs. If benefits are expected to be greater than costs, then the project is considered as economically beneficial (OECD, 2006). If not all beneficial policies can be implemented, e.g. because of financial constraints, the Benefit-Cost Ratio (BCR) might help to compare and rank a policy within a set of alternatives. Additionally, BCA can be regarded as control mechanism to avoid a waste of public funds by investments into economically adverse projects (Ahlheim and Rose, 1989).

Three rather obvious limitations of this procedure come to mind: First, the method requires a direct comparison of benefits and costs; therefore, all net changes in well-being of all individuals need to be expressed in monetary terms. For some factors, there is empirical evidence and some agreement on how to monetize them. For others, it is generally accepted that monetization would yield wrong certainty about the magnitude of their impact. Thus, there is a need for clear definitions which factors should be considered in the context of BCA, which factors should enter the decision making process outside of BCA, and which factors should not enter at all. Second, if politicians decide about a policy based on the BCR only, benefits and costs might be unequally distributed amongst the members of society: for instance, the policy could be disadvantageous for a major part of the population, or for influential circles. This could, in turn, lead to acceptance issues.[1] In this context, the way how results are presented

[1] This problem will be picked up later in Ch. 3.

to decision makers becomes crucial: should the impacts be presented as aggregates in units of money or can/should the decision maker additionally consider more disaggregated numbers in the original units of the factors? Third, the factors considered in the BCA have explicitly or implicitly been defined as 'relevant' by politicians or modelers. Also their weights have been determined. Such top-down approach is questionable at times where people are becoming eager to participate more in governmental decisions.

1.1.3 Transport Planning and Policy in the 21st Century

At the beginning of the 21st century, many countries are experiencing major changes in commodity flows and in people's mobility. On the one hand, a globalized world is evolving where division of labor and new markets lead to a strong increase in freight transport. On the other hand, people's mobility patterns are shifting: more leisure related travel in the industrialized countries, more demand for motorized transport in the developing countries. Therefore, all nations face major challenges in the field of transport infrastructure and policy planning. Most industrialized countries show a stagnating or even shrinking demography, together with a rather slow economic development. One of the core challenges will be how to efficiently maintain the quality of transport supply with decreasing financial means. In many developing countries, the challenges are even more pronounced. If governments want to provide the same quality of service in transport to their population as in the industrialized world, there is a strong need for new solutions. One might argue that a mobility based on private cars would be impossible due to scarcity of fossil energy sources and, above all, scarcity of urban space in the metropolitan regions.

The changes in commodity flows and people's mobility are expected to lead to an increase in transport-related negative externalities such as congestion, local pollution, and climate change. Therefore, political intervention on a global scale will be needed on very different levels, referred to as the 'Four E':

1. Engineering
2. Education
3. Enforcement
4. Economy

Engineering includes mainly technical solutions and has always been very popular in transport science. This is due to the fact that, historically, transport science evolved from civil engineering. Today however, it is widely accepted that, e.g., simply expanding transport infrastructure does not yield the desired results. In the context of alternative engines and more fuel efficient cars, this field is still evolving. Education is related to modifying behavior by increasing (environmental) awareness. Enforcement comprises all regulative measures, such as speed limits or environmental zones in cities. Economy refers to policies that correct market failures by (monetary) incentives; the most prominent example is a city toll. Especially the last field has gained more and more attention over the last decade in transport science, but also in practice. Even though the basic idea behind has been well-known for more than a century, the implementation of complex toll schemes has technically not been feasible until a decade ago (Lindsey and Verhoef, 2001).

In order to evaluate these political interventions, the BCA method is required and therefore used as decision support tool in transport planning (see, e.g., European Commission, 2008; OECD, 2006). The shift from technological and regulatory measures towards policies that focus on behavioral changes can be seen as a first indicator that the state-of-the-practice in BCA needs some revision. Additionally, the modeling of individual mobility behavior, e.g. in the field of Discrete Choice Models, has experienced strong improvements with the increasing computational resources (OECD, 2006). This also pushed the development of transport models with focus on the individual traveler (or agent) rather than on aggregated traffic flows. These models are able to predict the impacts of a policy on a single individual with all her constraints along the activity chain over a given time period. Individual reactions are not limited to route choice and mode choice any more, but can be extended by departure time choice, or (secondary) activity location choice within the same model. These new developments allow for a more sophisticated analysis of the policies under consideration.

Apart from the shift in policy design, there seems to be another transition especially in the industrialized world: one can observe a decreasing acceptance of top-down decisions in transport planning. People demonstrate heavily against big infrastructure projects. To name some prominent examples: the train station ‘Stuttgart 21’ in south-west Germany, the rail connection ‘TAV’ from Lyon to Turin, the airport ‘Notre-Dame-des-Landes’ in Brittany, or the fast rail connection ‘HS2’ from London to the West-

Midlands. All these projects are facing major acceptance issues even though for many of them, a comprehensive BCA has shown that the project is economically beneficial. This can be seen as an indicator that the public participation processes might have been insufficient, and that the typical numbers presented to politicians do not reflect these acceptance issues. Again, these developments show that the state-of-the-practice BCA needs some revision.

To summarize, one can state that at the beginning of the 21st century, the individual is becoming more important in many ways: on the one hand, transport models are able to deal with heterogeneous users which are affected by the same policy in very different ways. On the other hand, public participation and transparency of political decisions are becoming crucial factors that can decide about success or failure of a policy. It therefore appears necessary to re-think and adjust transport policy appraisal schemes to the changing requirements. This thesis can be regarded as a step into that direction. It will try to identify improvements for decision makers and the public that can be obtained by including heterogeneity of users into agent-based transport simulations.

1.2 Research Questions

1.2.1 Individual Trade-Offs and Benefit-Cost Analysis

Heterogeneity of users in transport models can be captured in many ways. Individuals have different activity plans and locations, different trip purposes, different desired departure times, different income, different car types, etc. Some of these characteristics influence the *attributes* of their travel alternatives. For instance, a big car might lead to a more expensive car trip than a small car. Other characteristics influence the *preferences* of the individual, or in other words, their perception of the attributes in each travel alternative. For example, assume a person with low income and a person with high income. The low-income person chooses a bike for the way to work and the high-income person rather chooses a taxi for the same trip. The reason here could be that monetary costs of travel alternatives are perceived differently among the two individuals. If the behavioral model does not account for heterogeneity in user preferences, the model might predict both individuals to take public transport.

The empirical basis to capture these individual trade-offs is provided by Discrete Choice Models (Ben-Akiva and Lerman, 1985; Train, 2003) that use data from Stated Preference (SP) and/or Revealed Preference (RP) surveys (see, e.g., Börjesson and Eliasson, 2014; Jara-Díaz et al., 2008; Mackie et al., 2003; Tirachini et al., 2014; van den Berg, 2011; Vrtic et al., 2008). When a policy comes into place that changes the attributes of travel alternatives, individuals are expected to face new trade-offs and adjust to the new supply accordingly. An example on the aggregated level might be the following:

- Increasing the operating speed of public transport reduces travel time for public transport users.
- Users of other transport modes might switch to the improved public transport facility since it has become competitive for them.
- If the other transport modes were congested, the congestion relief by mode switchers reduces travel time for the remaining users of the other transport modes.

The aggregated effect might be predictable without heterogeneous users, e.g., predicting the number of mode switchers. If we are interested in *who* is changing mode and who is not in order to provide more profound insights for policy makers, then differences in the individual trade-offs need to be included. Additionally, the question arises if and how these differences need to be captured by the subsequent economic evaluation. This leads to the first two research questions of the thesis:

Question 1:
For the behavioral model *of the transport simulation, what are the advantages and disadvantages of considering heterogeneous user preferences?*

Question 2:
For the subsequent economic analysis *of policy measures, which impacts does the above model have in case of:*

(a) a non-monetary policy?

(b) the optimization of a pricing policy?

1.2.2 Environmental Externalities

Apart from individual trade-offs and their economic valuation, a sophisticated BCA also includes externalities (OECD, 2006). Negative externalities are costs that are not included in the decision making process of individuals. That is, they are not compensated through a market mechanism and therefore reduce the efficiency of the economy (Lindsey and Verhoef, 2001). In traffic, they comprise costs for society due to congestion, local pollution, global warming, noise, and accidents. To give an example: a person chooses a car for her way to work. She calculates her own time loss which is the expected travel time. But her being on the street increases travel time for other people. However, the person does not have to compensate the others for their time losses that were caused by her. Changes in congestion costs, which result from changes in travel times for users, are therefore to a large part inherent to the transport market. That is, these costs are implicitly considered in the BCA. In contrast, local pollution, global warming, noise, and accidents also affect individuals outside the transport market. Even though current estimates indicate for the European Union that congestion causes the largest part of negative externalities (see Maibach et al., 2008, p.103), there is some perception that local pollution and climate change need to be addressed as well; those become especially important for freight traffic. The need for further investigation also stems from the fact that the allowed thresholds, set by the European Commission (e.g., Directive 2008/50/EC), are exceeded in many European cities. For some developing countries, the estimates for external costs caused by local pollutants are significantly higher. Beijing, for instance, already today faces pollution costs that are almost at the same level as congestion costs (Creutzig and He, 2009).

Clearly, not every person emits the same amount of air pollutants. The individual pollution level is dependent on several factors: transport mode, route, vehicle type, distance traveled, time of the trip, speed, etc. Thus, in the context of a transport model that deals with heterogeneous users, there is a need to include these factors for the identification of individual pollution levels. This part of the thesis therefore concerns the technical feasibility of integrating heterogeneous user attributes into an agent-based simulation. In terms of policy appraisal, it then becomes crucial whether the person-based approach improves our understanding of the interaction between car travel demand and emission level. The above considerations

are formulated in the following two research questions:

Question 3:
In a large-scale dynamic traffic flow simulation, how can heterogeneous user attributes, such as vehicle type, be used for the calculation of person-specific pollution levels?

Question 4:
Given a price change in car user costs, are aggregated price elasticities of emissions higher than those for car travel demand? If yes, can a spatially disaggregated effect be observed?

1.2.3 Internalization

The identification of individual pollution levels now makes it possible to internalize the external emission costs. Internalization is a concept developed by economists, which in principle aims for a 'true' price of transport (Pigou, 1920). The true price is composed of two parts: First, the price the person already paid in terms of monetary costs, lifetime, dissatisfaction, etc., referred to as Marginal Private Costs (MPC). Second, the price that has been paid by others resulting from the action of that person, e.g., longer travel times, health damages, etc. The second part reflects the negative externalities, and is equal to the difference between Marginal Social Costs (MSC) and MPC (Lindsey and Verhoef, 2001). If one could calculate all negative externalities that a person was causing to society in monetary terms, and then make that person pay the price, this would make the person include these effects in the choices. This concept has extensively been studied by transport economists, mainly with focus on congestion costs (Arnott et al., 1993; Lindsey and Verhoef, 2001; Vickrey, 1969). However, because of the complex nature of the calculation and very high implementation costs, it has always been a rather theoretical concept (Verhoef, 2001). The main argument here is, that even if the calculation of person-specific external costs was feasible, nobody would understand the ever changing pricing scheme. In turn, it is highly unlikely that the awareness of external costs would increase, if people do not know what exactly they are paying for, and how to avoid these costs.

In an agent-based transport simulation, however, one could aim for the comprehensive calculation of external costs. One could also make agents pay the true price and re-think their decisions based on full information

provided by the simulation. The outcome would be a simulated first-best air pollution toll. This simulated optimum could be used as a benchmark for the evaluation of real-world policies by showing the maximum potential efficiency gain. Therefore, this thesis addresses the following last two research questions:

Question 5:
In an agent-based large-scale transport simulation, how can the internalization of external air pollution costs be modeled on an individual level?

Question 6:
Does the economic analysis of a simulated first-best air pollution toll improve the evaluation of regulatory measures?

1.3 Research Approach

As explained in the beginning of the introduction, this thesis is concerned with the identification of improvements in applied BCA that can be obtained when introducing heterogeneous user preferences and user attributes into the Multi-Agent Transport Simulation (MATSim). The software is chosen for several reasons: On the one hand, it is based on agents or individuals; together with the high degree of modularity, this facilitates the integration of extensions such as the necessary individualized behavioral model. On the other hand, it provides a mesoscopic dynamic traffic flow model which is needed for the sophisticated calculation of externalities such as congestion (Engelson et al., 2012) or exhaust emissions (Wismans et al., 2013). Furthermore, the software is able to deal with large networks and several million individuals at a resolution of 1 *sec* time steps. Finally, MATSim by default offers performance functions in order to compare travel alternatives. These functions can be interpreted as utility functions from microeconomics: The attributes of alternatives, such as monetary costs or travel time, result from the simulation of the physical environment. The weight of each attribute can be interpreted as preference and, e.g., reflects the impact of monetary costs or travel time on utility.

In order to answer the above Research Questions, several extensions and plug-ins have to be implemented, integrated, and tested (see later in Ch. 2). The thesis uses these extensions in several Case Studies of two different large-scale real-world scenarios: the metropolitan areas of Zurich

(Switzerland) and Munich (Germany). The following sections provide an overview of the necessary steps in each scenario. In addition, limitations of the models and effects on the interpretation of results are pointed out.

1.3.1 Heterogeneity in User Preferences

In the Zurich scenario, the focus is on heterogeneous *user preferences* (see Fig. 1.1). The heterogeneity is expressed by an income-dependent marginal utility of money in the person-specific utility function. This essentially reflects the fact that monetary price changes affect people with different income differently in their well-being. In order to answer Research Questions 1 and 2 in Case Studies I to III (Ch. 3), the following sequential steps are conducted:

1. Estimating an income-dependent utility function for the behavioral model. Survey data is provided by the Institute for Transport Planning and Systems at ETH Zurich (Vrtic et al., 2008). The results are individual utility functions similar to Kickhöfer (2009), which capture the effect that the marginal utility of money decreases with increasing income.

2. Extending MATSim in such way that every agent has its own *travel disutility calculator* (relevant for routing), and its own *utility function* (relevant for learning).[2]

3. Generating an income distribution for agents from a Lorenz curve and from income medians of the municipalities under consideration.

4. Testing the implementation in a simple commuter mode choice scenario.

5. Running the implementation in the large-scale scenario of the Zurich metropolitan area. Validating against the income-*in*dependent scenario described in Chen et al. (2008).

6. Running the implementation again in the large-scale scenario, this time with a non-monetary policy: an increase of public transport operating speed by 10%.

[2] For a description of the iterative simulation procedure of MATSim, please refer to Sec. 2.2.1.

7. Running the implementation again in the large-scale scenario, this time with a monetary policy: a distance-based morning peak toll with different fixed toll levels.

8. Analyzing and interpreting the results.

1.3.2 Heterogeneity in User Attributes

In the Munich scenario, the focus is on heterogeneous *user attributes* (see Fig. 1.1). The heterogeneity is expressed by person-specific car types which, ceteris paribus, result in person-specific exhaust emissions. That is, given a certain time on certain street with a certain traffic state, a person with a fuel consuming car emits more emissions than a person with a fuel efficient car. In order to answer Research Questions 3 and 4 in Case Study IV (Ch. 4), the following sequential steps are conducted:

1. Creating and validating the MATSim scenario for the metropolitan area of Munich byu sing different data sources for network, population, car ownership, etc.

2. Developing and implementing the emission modeling tool. The features and requirements of this novel approach are:

   a) Linkage of MATSim's traffic flow model with the database of the Handbook on Emission Factors for Road Transport (HBEFA).

   b) Calculation of vehicle-specific, time-dependent cold and warm emissions.

   c) Applicability to large-scale scenarios.

   d) Re-usability and transferability to other scenarios.

3. Testing and validating the implementation in a single street scenario.

4. Running the implementation in the large-scale scenario of the Munich metropolitan area.

5. Running the implementation again in the large-scale scenario, this time assuming different increases in car user costs.

6. Deducing aggregated price elasticities of car travel demand and exhaust emissions.

7. Deducing spatially disaggregated effects in changes of car travel demand and exhaust emissions.

8. Analyzing and interpreting the results.

1.3.3 Heterogeneity in External Cost Pricing

For the Munich scenario, Case Study V compares the impacts of a first-best exhaust emission toll to a regulatory measure (see Fig. 1.1). In order to answer Research Questions 5 and 6, vehicle-specific, time-dependent emissions from the MATSim emission modeling extension are used in Ch. 5. These are computed every time a traveler leaves a road segment. Based on this, external air pollution costs are calculated for Sulfur Dioxide (SO_2), Particular Matter (PM), Nitrogen Oxides (NO_x), Non-Methane Hydrocarbons ($NMHC$), Carbon Dioxide (CO_2), following external emission cost factors provided by Maibach et al. (2008). For the internalization of external air pollution costs on an individual level, travelers are directly charged with the resulting costs when leaving a road segment. The necessary technique is developed in this thesis and requires two changes to the default MATSim behavior. First, emission costs need to be internalized into the individual's utility calculation, as attributes of the relevant travel alternatives. Second, the *expected* emission costs of possible travel alternatives need to be fed into a module that generates possible routes for the individual. Finally, the outcome of this internalization policy is used in order to compare travel patterns and economic impacts to those of a regulatory measure—a speed limitation to 30 km/h in the inner city of Munich.

1.3.4 Research Scope

Given the complex nature of individual decision making and the large number of interactions between individuals in the physical world of the model, the scope of this thesis has to be limited in several respects. These limitations are captured by the following list. It shows, e.g., where models are still insufficient or where other models could be integrated with the ones used in this thesis. The list is meant to provide an overview of research opportunities that can be tackled by the author or other researchers in the future.

1. *Reference Scenarios*

   a) *Population Synthesis*: Initial activity patterns for passenger traffic are taken from micro-census information and mobility surveys. The approach of generating a full population from these samples is simplified, e.g. by 'cloning' individuals and randomizing activity locations and departure times. Over the last years, much more sophisticated models in the area of population synthesis have been developed and are getting operational(see, e.g., Bhat et al., 2004). Those should be used in the future in order to get the synthetic population statistically unbiased.

   b) *Freight Traffic*: The Zurich scenario focuses on passenger traffic and does not explicitly account for freight traffic. This might be reasonable since for the Zurich scenario where environmental impacts are not examined. In the Munich scenario, demand for freight transport is explicitly included in the demand, even though in a very simplified way: there is no supply chain model, and trucks only perform one single trip during the day. In terms of policy responsiveness, this is a major drawback (see below in 'Behavioral Modeling').

   c) *Car Allocation Model*: In the Zurich scenario, every person has a car available. Therefore, the modeling of public transport captives is not possible. In Munich, car ownership is modeled on a household basis. However, there is no vehicle assignment module which takes into account intra-household decision making. Thus, it might happen that the same car is assigned to two or more agents of the same household at the same time.

   d) *Validation*: All scenarios are validated against real-world count data. Thus, the reference scenarios are expected to sufficiently reproduce real-world travel patterns and traffic flows so that forecasts of policy effects are *structurally* correct. However, the exact figures are not meant to be definitive, fully realistic or imply any suggestions for policy makers in the corresponding cities. For a true authoritative forecast, one would need to work more on the calibration and validation part of the scenarios. There are academic attempts to automatize the calibration process of reference scenarios within the MATSim framework (see, e.g.,

Flötteröd et al., 2011). However, it is up until now still unclear how this might influence the forecast ability of policy scenarios.

2. *Public Transport (PT)*: In all Case Studies, PT is not modeled in detail. Instead, an approximation for travel times and distances is used as explained in every Case Study. Additionally, PT is assumed to run continuously, without capacity constraints, and emission free. For successful implementations of detailed PT models in the MATSim framework, please refer to Rieser (2010), Neumann et al. (2014) or Erath et al. (2012).

3. *Emission Modeling*

   a) *Emission Types*: Cold-start emissions depend on ambient temperature, warm emissions on road gradient. The emission modeling tool does—as of now—not account for these effects.

   b) *Traffic Flow Model*: Because of the simplified nature of MATSim's traffic flow model, the location of a car on a link is unknown. The advantage is that the model is able to deal with large networks and a large number of vehicles. The drawback is that acceleration and deceleration of vehicles is not part of the model. To correct for this, the emission modeling tool reconstructs the part of a link with stop&go traffic by an approximation. According to other studies, this mesoscopic approach is not necessarily worse in predicting exhaust emissions than detailed traffic flow models that account for acceleration and deceleration patterns (Song et al., 2012).

4. *Choice Dimensions*: Depending on data availability, there are different choice dimensions available for the scenarios Zurich and Munich. In both scenarios, agents can choose to change their car route as a reaction to policies. Also, they are allowed to change their transport mode between car and PT for the whole day (Zurich) or for one or more trips during their day (Munich), respectively. Departure time choice is only relevant for the Zurich scenario where time-critical policies are investigated. Long-term choices in vehicle type are approximated in the context of a sensitivity analysis (see Ch. 5). Effects of land use changes or secondary location choices are not part of this thesis. For academic attempts to integrate these choice dimensions in the

MATSim framework, please refer to Nicolai and Nagel (forthcoming) or Horni et al. (2012).

5. *Behavioral Modeling*

   a) In the Zurich scenario, each agent has an individual utility function that is used to evaluate the performance of travel alternatives (individual user preferences). These preferences are obtained by estimating the parameters for a Multinomial Logit (MNL) model from survey data.

   b) For the Munich scenario, no such data source is available. Therefore, the behavioral parameters are taken from the Zurich estimation or from an Australian study (Tirachini et al., 2014), respectively. For each reference scenario, the Alternative Specific Constant (ASC) is re-calibrated by a parametric validation of traffic flows against count data.

   c) In both scenarios there is no explicit behavioral model for freight transport or commuters. Both might have very different preferences (e.g. higher Value of Travel Time Savings (VTTS)) than urban travelers. In terms of policy responsiveness, this is very likely to yield biased, probably too elastic user reactions. There are some VTTS studies that could provide the necessary parameters (de Jong, 2000; Zamparini and Reggiani, 2007), but there is also some indication that the Value of Travel Time Reliability (VTTR) might in some cases be more important for decision making in this demand segment (Wigan et al., 2000). Thus, this field of research seems to be a very interesting and important one for the future.

6. *Economic Evaluation*

   a) *Utility Changes*: In the Zurich scenario, changes in utility are captured by the difference between the agent's executed plan of the policy scenario and the executed plan of the reference scenario. In order to evaluate the utility change of the *choice set*, changes in utility are in Munich captured by the difference of the logsum term of all plans of each agent. There is, however, some indication that the choice sets computed by MATSim are neither complete nor uncorrelated. Additionally, the choice set

generation is biased by the method in which plans are removed from an agent's memory: up until now, the plan with the lowest utility is removed whenever the maximum number of plans are reached for an agent. This increases the likelihood that the final choice set is correlated, i.e. containing only plans that are very similar to the best plan (see Prato, 2009, for a review on correlation of routes). Hence, future research should account for these two issues. First, more heterogeneity needs to be introduced into the choice set generation, e.g. by producing very different plans. Second, the method for plans removal needs to be based on a logit model where the difference in utility enters, similar to the approach of selecting plans for execution. A possible solution that adds a disutility for similarity of options could be based on a method called 'pathsize logit' (see Ben-Akiva and Bierlaire, 1999; Frejinger and Bierlaire, 2007, for a possible solution in route choice). Once a valid choice set is (approximately) obtained, the logsum calculation is probably the way to go in terms of utility calculation (Nagel and Flötteröd, 2012).

b) *Monetization*: The monetization of utility changes requires a uniform marginal utility of money. This essentially means that, in terms of utility, it does for instance not matter if a person spends one *EUR* for gasoline or one *EUR* for a public transport ticket. In the preference estimation, this can be obtained by *forcing* all cost related parameters of all alternatives to the same value. Most choice experiments, however, indicate that the purpose of where a person spends money actually influences utility. That is, one obtains mode-dependent marginal utilities of money (see, e.g., Vrtic et al., 2008). In this thesis, the marginal utility of money is forced to the same value wherever an economic evaluation of policies is performed. Only in Ch. 4, the additional degree of freedom is allowed. To the knowledge of the author, there is no best solution to this problem in the literature, the single value for the marginal utility of money is rather a necessary convention.

1.4 Outline

This thesis consists of six chapters. After the introductory Ch. 1, Ch. 2 exhibits the methodological part which is composed of three steps: First, it provides a literature review on the microeconomic foundations of economic policy appraisal. In particular the theory behind BCA is explained, recently developed guidelines for project appraisal in industrialized countries are discussed, and criticism and limitations are presented. Second, the necessary models are developed with the goal to capture heterogeneous user preferences and user attributes within a multi-agent transport simulation. This involves, on the one hand, setting up a model that allows for person-specific marginal utilities of money. On the other hand, it involves the creation of a model that provides a sophisticated calculation of vehicle-specific, time-dependent warm and cold exhaust emissions. Third, the chapter presents possible approaches on how economic policy appraisal can be performed in an agent-based context where individuals optimize their travel behavior with respect to a Random Utility Model (RUM). Ch. 3 to Ch. 5 investigate the Research Questions with the help of different Case Studies, as illustrated in Fig. 1.1. Ch. 3 investigates the impact of heterogeneous user preferences on the calculation of aggregated and disaggregated welfare levels, both, for a non-monetary and a monetary policy. Ch. 4 compares aggregated price elasticities of demand and aggregated price elasticities of emissions, and looks at the spatial effects that can be observed when considering vehicle-specific exhaust emissions. Ch. 5 focuses on external cost pricing, in particular on exhaust emission pricing. A first-best air pollution toll is used to internalize external costs related to exhaust emissions, and implications on the evaluation of regulatory measures are presented. The thesis closes with Ch. 6 where answers to the Research Questions are deduced by summarizing the main findings and contributions of the empirical chapters. This final chapter also provides an overview about policy implications and venues for further research.

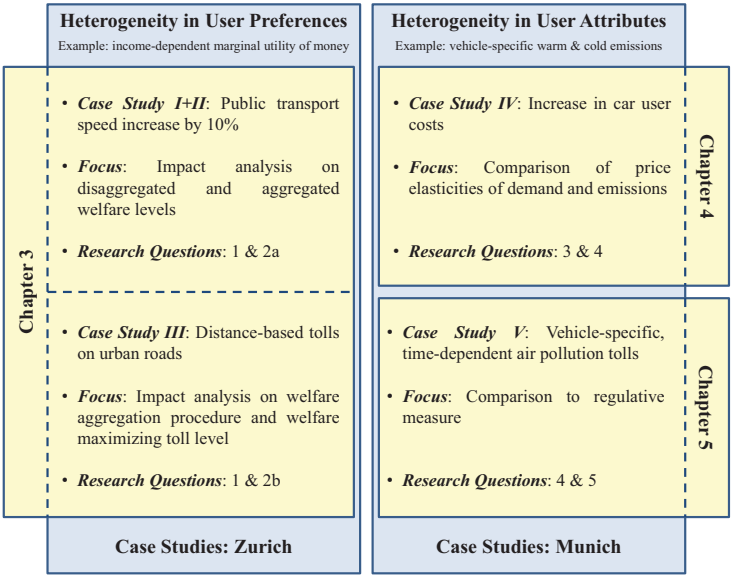


Figure 1.1: Outline of the thesis.

Chapter 2

Methodology

This chapter develops the methodology that is applied in the subsequent Case Studies for economic policy appraisal and emission modeling. The chapter consists of several parts:

The first part is a literature review on the microeconomic foundations of economic policy appraisal, in particular Benefit-Cost Analysis (BCA). It will point to recently developed guidelines for project appraisal in industrialized countries and discusses criticism and limitations as well as the treatment of user heterogeneity in these economic appraisal schemes.

In the second part, the software for transport simulation and emission modeling is presented: on the one hand, the agent-based transport model which is used for all simulations in this thesis. The focus of the presentation hereby is on the mental layer of the software where the behavioral learning of agents takes place. On the other hand, the emission modeling software is described which has been developed as part of this thesis.

The third part discusses the methodology for economic policy appraisal in an agent-based context where individuals optimize their travel behavior with respect to a Random Utility Model (RUM). This discussion is based on the information gathered in the first two parts of the chapter.

2.1 Background: Economic Policy Appraisal

The main tasks of politicians and decision makers in a representative democracy is to review and change policies in place, and initiate new policies. The decisions on how to distribute public funds between different policy options are crucial for economic growth and the development of

welfare of a society (OECD, 2006). The investment of economic resources at the time of the decision is coupled with the hope for benefits in the future. Different policies with different time horizons are characterized by very different uncertainties in terms of future benefits or Social Return On Investment (SROI). As European Commission (2008) state,

> "[t]he economic returns from investing in telecoms or in roads will be enjoyed by society after a relatively short time span following project completion. Investing in primary educations means betting on the future generation and involves a period of over twenty years before getting a result in terms of increased human capital. Preserving our environment may require decision-makers to look into the very long term, as the current climate change debate shows."

The above decision on which projects should be realized becomes even more complicated if one considers *opportunity costs* in addition to different time horizons and uncertainties: investing in one project implies to give up the opportunity to invest the same money in other project(s) (von Wieser, 1927; Williamson, 1993). The future benefits of these other project(s) will never accumulate which makes an ex-post comparison to the benefits of the realized project impossible.

For these reasons, decision support models are needed which provide the quantitative and qualitative basis for investment decisions. These models try to capture the impacts of policies on society as realistic as possible, but also only as detailed as necessary. The complexity of reality forces every descriptive model to approximations and assumptions which, in turn, result in a limited forecast ability. Additionally, it seems impossible and not very wise to attempt an ex-ante evaluation of every imaginable policy for comparison.[1]

For the appraisal of the policies under discussion, different approaches are used in practice. According to European Commission (2008), a sophisticated appraisal method consists of the following steps:

1. Presentation / discussion of the socio-economic context and the objectives

2. Clear identification of the project

[1] This shows the importance of the policy generation process which describes how policies are put on the political agenda. The investigation of this process is not focus of this thesis.

3. Study of the feasibility of the project and of alternative options
4. Financial analysis
5. Economic analysis
6. Risk assessment

For the economic analysis step, most industrialized countries have implemented some sort of BCA. This method will be described in more detail in the next sections.[2]

2.1.1 Benefit-Cost Analysis: Motivation

The basic idea behind this quantitative method is that one compares the aggregated (discounted) benefits of a measure to the total (discounted) costs. If benefits are expected to be greater than costs, then the project is considered as economically beneficial (OECD, 2006). Even though the approach is often criticized from different angles (see later in Sec. 2.1.4), the necessity of such an appraisal framework is highlighted by the following quote by Jara-Díaz (2007, p. 81):

> "Other things being constant, cheaper, faster, safer or more comfortable forms of transport make people feel better off. But improving transport systems requires funding which could have been assigned to other important needs. Benefits of better transport are behind the former phenomenon; costs are behind the latter. This means happiness on one hand, resources on the other.
>
> We need to express a change in well-being in monetary terms, so we can compare that value with costs in order to determine if a project is worth the effort, and if so, rank it within a set of alternatives, which is a common and very important part of regional and urban planning processes.
>
> It is indeed as challenging as it sounds, but the only other option is to just fund and build the projects and then hope for the best, which does not sound very appealing."

[2] Other methods, such as Multi-Criteria Analysis or Cost-Effectiveness Analysis, sometimes replace BCA, or are used in addition. These methods are not further discussed in this thesis.

The last sentence emphasizes the importance of quantitative policy appraisal. Simply building projects and hoping for the best would mean that public funds are dedicated to projects in processes which might aim for other goals than increasing social welfare. Such processes would open doors for favoritism and corruption. In that sense, BCA can be seen as a control mechanism that helps avoiding a waste of public funds by investments into economically adverse projects (OECD, 2006).

The above quote narrows the decision problem already down to the transport sector. In theory, the methodology of BCA is designed in such way that a comparison between all sectors of economy could be performed in order to answer questions like: "Is it advisable to invest money into a new metro line or rather into the educational system?" But in practice, the uncertainties of this appraisal method along with the necessary assumptions limit the focus of the approach. Additionally, a cross-sector comparison would create strong incentives to influence the sector-specific attributes for BCA instead of discussing openly how much money should be invested into which part of the economy and why. The goals of the following sections are to review (i) the theoretical foundations of BCA, (ii) the practical applications in the transport sector, and (iii) the main critical issues related to this approach.

2.1.2 Benefit-Cost Analysis: Theory

The theoretical foundations of BCA are provided by welfare economics. The key question is whether a policy is worth the effort from an societal point of view, and is thus increasing social welfare (Bickel et al., 2006). According to Ahlheim and Rose (1989), the welfare level of a society can not be independent from the welfare levels of its members.

The basis for measuring welfare on individual level, i.e. for every person of the society under consideration, is *utility*. Utility can not be measured directly since it can—by definition—only be perceived by the individual itself. Utility is typically interpreted as *wellbeing* (OECD, 2006), *sophistication* (Samuelson and Nordhaus, 1992), or *happiness* (Jara-Díaz, 2007). Observing preferences of individuals can be used to build individual utility functions which capture the impact of different goods or attributes of goods on individual utility levels. Initially, these intra-personal levels of utility only yield a ranking of the different options. That is, utility is ordinal in scale, and the absolute difference in utility has no meaning. This directly

leads to the problem that inter-personal comparisons of utility levels are not allowed (Ahlheim and Rose, 1989). This limitation is not an issue per se, if only policies are considered where at least one person is better off afterwards, and no person is worse off (Pareto, 1896). This policy is then called *Pareto improvement* (also see Stiglitz, 1983).

However, in practice, it is very likely that a policy affects some individuals positively and others negatively. Therefore, Kaldor (1939) and Hicks (1939) developed the so-called Kaldor-Hicks compensation test: The economists propose to investigate whether the winners would be able to compensate the losers. If the answer is 'yes', this policy would be a *Kaldor-Hicks improvement* or *potential* Pareto improvement. If the compensation took place, this would result in a true Pareto improvement. The advantage of this idea is that no inter-personal comparisons of utility levels are needed since the compensation only redistributes goods or income among individuals in such way that the losers are indifferent to the policy. Again, in practice, it may seem unrealistic to actually undertake these compensations. Unfortunately, investment decisions that rely on a potential Kaldor-Hicks improvement, which is based on hypothetical payments, do not result in a complete and transitive order of all potential states of society (Ahlheim and Rose, 1989). In the strict sense, the potential Kaldor-Hicks criterion can therefore only be used to decide whether a project is economically beneficial (e.g. SROI > 0), but a ranking of policies based on hypothetical payments remains problematic. Nevertheless, as will become clear in the following Sec. 2.1.3, BCA is often used for such project rankings since it claims to consider the trade-off between individual welfare levels of winners and losers. This might facilitate decisions about real-world policies, but is build on unstable theoretical assumptions. For more criticism on the methodology and further practical assumptions of BCA, please see later in Sec. 2.1.4.

2.1.3 Benefit-Cost Analysis: Practice

In the 1960s, Benefit-Cost Analysis entered the infrastructure and transport planning practice in the United States and the United Kingdom (Coburn et al., 1964; Haveman, 1965; Prest and Turvey, 1965). The main reason was the need for evaluation of the numerous infrastructure projects at that time, and, after World War II, the need to ensure that public funds are used efficiently (OECD, 2006). In contrast to the early infrastructure

projects during the Industrial Revolution, the state was now recognized to be responsible for planning and maintaining infrastructure, especially transport infrastructure. One could argue that private railway companies had already assessed projects with methods similar to BCA. However, the focus there was more on profitability from a business-management perspective. Along with the shift from private to public sector, BCA was needed to quantify economic benefits from an societal point of view (OECD, 2006). Even though the basic idea behind this appraisal method remained the same, the models describing human mobility behavior and revealing preferences from observations experienced rather strong changes and improvements during that period. Especially over the last three decades, data-driven models have made remarkable progress as a result of the increase in computing power. The following paragraphs will therefore give an overview about recent publications on the applied use of BCA.

Grant-Muller et al. (2001) revise for Western European countries the state-of-the-art in economic policy appraisal of transport projects around the year 2000. The authors argue that economic policy appraisal "is aiming at a moving target", and has experienced big changes since the late 1960s. The reasons for this development are eclectic: First, the focus of transport appraisal schemes has been extended and newer methods needed to cover environmental and broader economic impacts in addition to time and cost savings, or safety improvements (also see OECD, 2006). Second, they observe a shift from evaluating a single project for a single mode of transport towards projects that affect whole areas and multi-modal corridors. Third, the public has gained more direct political power. Therefore, the presentation of investment decisions to the often skeptical public puts the whole evaluation method under pressure: simple top-down decisions based on simple educated guesses by experts and decision makers are not accepted any more. In their work, Grant-Muller et al. (2001) find that scope and appraisal framework substantially differ among European countries. Even though there is some commonality in measuring and monetizing direct transport impacts, the national practice is influenced by the cultural and economic background of the country. For instance, the number of impacts that are included in the appraisal varies substantially. Some countries include environmental and socio-economic impacts into their appraisal scheme, some only present these impacts in addition to the BCA result, and others do both. Additionally, there are differences in the treatment of single- vs multi-modal evaluations, i.e. some countries have

entirely separate frameworks for different modes. Summing up, the authors conclude that it has become "increasingly desirable to share best-practice appraisal principles at the European level", and probably necessary to develop more unified guidelines since member states will start to compete more and more for funding by the European Union (EU). Thus, they identify a need for comparability of projects that have been evaluated according to the same appraisal method.

Bickel et al. (2006) pick up this idea and develop—based on the analysis of the different existing appraisal schemes in the EU—harmonized guidelines for project assessment for trans-national projects in Europe. These guidelines are also applicable for national transport project appraisal, and thus, can be seen as a first step towards a more harmonized appraisal approach in Europe. The authors provide guidance for the evaluation of the following elements: treatment of non-monetized impacts, intra-generational equity issues, treatment of risks and uncertainty, the marginal costs of public funds, producer surplus of transport providers, Value of Travel Time Savings (VTTS), value of accident risks, environmental costs, and indirect impacts of infrastructure investments. This list already indicates that the approach tries to cover a broad range of impacts which have been found to be relevant when assessing the national practices.

In the same mindset, European Commission (2008) offer guidance on project appraisals. Following these guidelines is to some extent mandatory when national projects apply for funding from the EU. This can be seen as a rather smart move, since it creates incentives for a true harmonization of (at least project related) appraisal schemes. For this reason, it did not take long until the member states transferred these guidelines into country-specific recommendations when applying for European funds, e.g. European Regional Development Funds (ERDF). For Germany, these guidelines are described by isw (2009) and IVV and Aviso (2009). The proposed performance indicators are financial Net Present Value (NPV), economic NPV, and Benefit-Cost Ratio (BCR). The first indicator describes the investment from a business-management perspective, by deducing the expected financial costs from the discounted expected revenues. The second indicator calculates the same figure, but is using discounted social benefits and costs instead of revenues and financial costs. This indicator already allows to decide whether the project is worth the effort from a societal perspective. For a ranking and a decision among different alternatives under (e.g. financial) constraints, typically the last indicator is used: it depicts

how many *EUR* per invested *EUR* are expected as social benefit over the whole project duration (OECD, 2006).

Just recently, Mackie and Worlsley (2013) published a technical report on international comparisons of transport appraisal practice. They state, only a bit more than a decade after the paper by Grant-Muller et al. (2001) that "[w]hile there are differences of values, emphasis and content, the similarities far outweigh the differences. [...] Progress has been made in the treatment of significant components such as the evaluation of reliability, crowding, carbon and other emissions and wider economy impacts". In that sense, the efforts by Bickel et al. (2006) and European Commission (2008) seem to have paid off in terms of getting the appraisal methods more homogeneous.

On the downside, the authors claim that the process on how the appraisal results enter the decision making process is often not transparent. Additionally, there is some indication that the report is omitting some particularities of the country-specific evaluation methods: for instance Germany, up until now, still using an evaluation approach which is rather based on resource consumption than on the aggregation of individual benefits (Bruns and Chaumet, 2008; Helms, 2000; Nagel et al., 2012; Winkler, 2011). The current German approach mainly focuses on travel time and monetary resource cost savings. The user perspective is not represented adequately. To give an example: Assume a policy which makes traveling from A to B faster but less comfortable. If the appraisal method only considers travel time as relevant resource, then the project's benefits are overestimated by omitting discomfort, which clearly is a decision variable for individuals.

The above issue is related to the question on how closely the underlying transport model needs to be in line with the subsequent economic evaluation. To the knowledge of the author of this thesis, there is no guideline or framework that investigates the impacts of possible (in)consistencies between the behavioral parameters of the transport model and the economic parameters of the evaluation method. This might be due to the fact that, historically, transport modeling has been performed by a different community than economic evaluation. In the past decade, however, some attempts can be identified to use Discrete Choice Theory both for behavioral modeling and economic evaluation (see, e.g., Daly et al., 2008; de Jong et al., 2007). Having regard to this development together with the shift towards multi-modal, elastic demand models, which possibly capture agent-specific preferences, the above question becomes a crucial one, especially for the present thesis; it will therefore be treated in Sec. 2.3.

The next section will now present the most common criticism on BCA, of which most are relevant when performing welfare analysis in an agent-based context.

2.1.4 Benefit-Cost Analysis: Criticism

Despite the numerous applications of BCA in transport planning, this method has often been criticized from different angles (OECD, 2006). Some of this criticism are more related to the theory behind it, others rather question assumptions that are made in practice. It therefore seems important to discuss the results of a BCA against the background of these limitations since they might influence the results. In that sense, a BCR might be a first indicator whether a project is worth the effort, but additional indicators need to be presented in order to capture the whole picture. The following paragraphs present a non-exhaustive list of concerns raised in this context together with some discussion of the issues and their importance for the present thesis. The list is based on the compilations by van Wee (2012) and Beukers et al. (2012). It is significantly extended by other literature readings, reasoning, and discussions with colleagues and other scientists.

Individual Gains and Losses The utilitarian measurement of utility typically assumes differentiable individual utility functions, i.e. a single value for the derivative of the function at the operating point. However, Prospect Theory finds that gains are perceived differently than losses; the latter are perceived more strongly, and this would have a rather strong impact on the results when calculating the necessary Kaldor-Hicks compensation (Avineri and Prashker, 2003; Kahneman and Tversky, 1979). To the knowledge of the author, there is no standard way of integrating this finding into the evaluation method. Assuming a non-linear utility function, the derivatives of the utility function at the reference point *after* the policy could also be used for evaluation. This is related to the question why, empirically, willingness-to-pay and willingness-to-accept differ (OECD, 2006). A possible consequence is that it might not always be correct to use an unambiguous VTTS in evaluation (Daly, 2013).

Measuring Utility, Aggregation As mentioned earlier in Sec. 2.1.2, utility can only be perceived by the individual itself. Random Utility Theory, initially applied to transportation by McFadden (1975), combines the

assumption of rational behavior with utility components that are random from the researcher's perspective. With this theory, it became possible to quantitatively predict choices that are irrational for the observer of an individual (Ben-Akiva and Lerman, 1985; Train, 2003).[3] Even though this is a big step towards consistency between descriptive models and observed behavior, the question on how to aggregate individual welfare changes still remains. There are different ways of doing this, closely related to the question whether income or time equivalents are used (see Sec. 2.3.3). The choice between these two options will influence the results of economic evaluation, as will be shown in Ch. 3.

Allocative and Distributive Effects It has often been argued by economists that policies for improving allocative efficiency have to be strictly separated from policies with distributive goals (OECD, 2006). That is, the 'Social Optimizer' should not include distributive thoughts into the model, and simply maximize social welfare. Although it appears quite obvious that not the same level of mobility supply can be provided to every member of society (equal distribution), a strongly unequally distributed supply is often perceived as unfair. The correct allocation is therefore influenced by more than social welfare maximization: it is determined by the socially accepted unequal distribution of resources.[4] In this context the *principle of proportionality* seems to be important: not too many members of society should feel disadvantaged and oppose the decision system. The correct procedure of evaluating transport projects therefore seems to be some kind of 'welfare maximization under constraints'. This would mean that some projects with a high benefit-cost ratio but regressive impacts on the welfare levels of the population could be ruled out beforehand. Another idea is to couple the project with true compensatory measures that offset these impacts in one or another way (Kanbur, 2007, 2008). In either way, with detailed models, distributive impacts of policies can and should be reported by additional decision supporting indicators, as will be shown in Ch. 4 and Ch. 5.

Heterogeneous Perception of Travel Times Stated preference studies indicate that the perception of travel times varies across individuals, depending on mode of transport, income level, purpose of the expense, and purpose

[3] For a short review on Discrete Choice Theory, see later in Sec. 2.3.1.
[4] C.F. Gethmann, personal communication.

of the trip. In consequence, VTTS vary accordingly. Depending on the scenario, the wage rate (Jara-Díaz and Guevara, 2003; Mackie et al., 2001), or the trip purpose and therefore time pressure (Börjesson et al., 2013) seem to be crucial factors. In order to describe human mobility behavior more accurately, advanced transport demand models use choice models with variations in individual preferences, i.e. variations in the marginal utility of money. It is then debatable whether the resulting differentiated income equivalents should directly be used for economic evaluation, since this would make BCA a rather undemocratic evaluation method: rich people would have a stronger weight on the outcome than poor people. For a discussion on how this effect can be captured in an agent-based framework, and on a different aggregation and monetization procedure, see later in Ch. 2.3.3. Possible impacts for decision support studies will be treated in Ch. 3.

Pricing the Priceless Apart from travel time and monetary costs, different BCA approaches try to capture the monetary effects of air pollution, noise, accidents, etc. Developing a proper methodology for these estimates has gained much attention in research over the last two decades. However, as of now, these effects do not have a strong, if any, influence on project ranking (for Germany, see BMVBW, 2003). Only a few studies find environmental externalities in the same amplitude as time costs (see, e.g., Creutzig and He, 2009). This might be an indication that the existing approaches of estimating these effects is not developed enough in order to capture the true costs for these factors. In this thesis, Ch. 4 and Ch. 5 are concerned about developing an evaluation method that can produce monetary and non-monetary indicators of changes in air pollution.

Political Influence and Ex-Post Evaluations Political Economy shows that decision makers try to influence the methodology of the evaluation method (OECD, 2006). This is also reflected in public opinion. Therefore, it is often believed that BCA only exists in order to justify projects that were already decided beforehand. Promising alternatives (e.g. solving the same problem with another transport mode) may not be considered. Additionally, in most countries, a lack in ex-post evaluations can be identified. Even though BCA is an ex-ante evaluation method, measured outcomes of realized projects could be used to calibrate the descriptive models, as well as to estimate the benefits of a measure in reality (see, e.g., Engelson et al., 2012). Clearly, both issues are related to the credibility of both, politicians

and modelers. Making the whole evaluation process, as well as data and modeling techniques more transparent and open would be a step in the right direction.

2.2 Modeling Transport and Emissions

2.2.1 MATSim

This section presents the Multi-Agent Transport Simulation (MATSim) that is used in this thesis for all simulations. It is the attempt of a summary that is universally valid for how the software is used in the upcoming chapters. The section is an edited version of previous descriptions of MATSim in Kickhöfer et al. (2011) and Kickhöfer and Nagel (2013); Kickhöfer et al. (2010, 2013). If the reader is interested in more detailed information on MATSim, please refer to the following contributions: Balmer et al. (2005, 2009); Cetin et al. (2003); Charypar and Nagel (2005); Charypar et al. (2007); Nagel and Flötteröd (2012); Raney and Nagel (2004, 2006).

MATSim is a software framework to implement large-scale agent-based transport simulations. For illustration purposes, Fig. 2.1 shows the iterative loop that characterizes the modeling approach with MATSim. Each traveler of the real system is modeled as an individual agent. Initial mobility patterns of each agent are generated based on survey data. Additionally, network data is needed as an input which describes the physical environment where agents interact. That is, 'Daily Plans', 'Scoring', and 'Re-planning' represent the mental layer, whereas 'Execution' exhibits the physical layer of the model. The following subsections will explain every step of the iterative loop in Fig. 2.1 in more detail.

2.2.1.1 Generating Plans (Daily Plans)

An agent's daily plan contains information about her/his planned activities including locations, durations and other time constraints. Additionally, it contains the transport mode, the route, the desired departure time, and the expected travel time of every intervening trip (= leg). Initial plans are usually generated based on micro-census information and/or other surveys. The plan that was reported by an individual is, in the first step, marked as *selected*. If desired, the agent can obtain more than one initial alternative plan.[5]

[5] This could be the case if MATSim is not used as a choice set generator and the whole relevant choice set (= all relevant alternative plans) is known or can be pre-

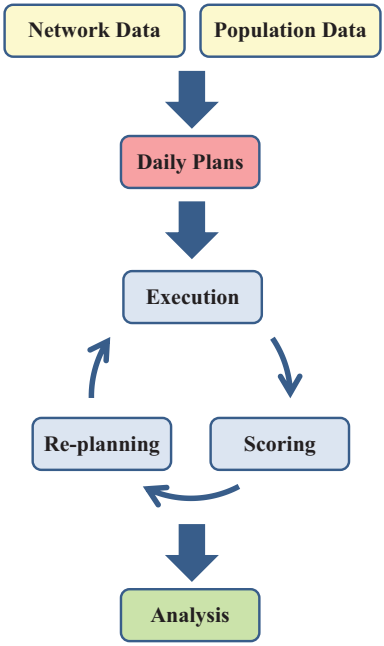


Figure 2.1: Transport simulation with MATSim. Source: Kickhöfer (2009).

2.2.1.2 Simulating Mobility (Execution)

The mobility simulation executes all selected plans simultaneously in the physical environment. The mobility simulation that is used in this thesis differentiates between car legs and legs that are conducted with other transport modes:

Car Traffic Flow Simulation It is implemented as a queue simulation, where each road segment (= link) is represented as a first-in first-out queue with three restrictions (see, e.g., Cetin et al., 2003; Gawron, 1998; Grether et al., 2012, for the most recent description): First, each agent has to remain at least for a certain time on the link, corresponding to the free speed travel time. Second, if there are other agents in front, the link travel time might

computed (Nagel and Flötteröd, 2012). This could also be the case if one considers only one transport mode per plan, and the non-reported alternative should always remain in the choice set (see, e.g., Ch. 3).

be increased by the *flow capacity*. It defines how many vehicles can leave the link per time interval. Third, the link storage capacity limits the the number of agents (or vehicles) on the link; if a link is filled up, no more vehicles can enter this link. Upstream vehicles remain in the queue of the upstream link even if the flow capacity of that link would allow the vehicles to leave. Thus, time losses in the queue result from other vehicles in front that did not yet leave the link.

Simulation of Other Modes All other transport modes in this thesis are simulated as *teleported modes*. At the time of writing, there are several implementations in MATSim for handling teleported modes. The following two[6] are used in this thesis:

- Travelers are teleported between activity locations with a configurable mode specific travel speed over a predefined distance. Distances are beeline distances multiplied by a factor, capturing detours due to network geometries. This is used for Case Study V in Ch. 5
- Travelers are teleported between activity locations with car travel times multiplied by a configurable mode specific factor. Car travel times result in this case from a routing on the fastest route in an empty network.[7] This is used for the Case Studies I to IV in Ch. 3 and Ch. 4.

The disadvantage of the first approach is that mode specific travel speeds might be valid for a certain area (e.g. the city area), but not for the whole metropolitan area. For instance, commuter traffic usually covers longer distances than inner-urban traffic, and therefore uses trains instead of buses. If the parameters are calibrated for inner-urban traffic, the approach overestimates public transport travel times for commuters. The disadvantage of the second approach is that policy changes to the car network implicitly change the public transport travel times. When analyzing speed limitations for cars (see, e.g., Ch. 5), this would bias the results. In both

[6] A third implementation for handling Public Transport (PT) as teleported mode is called 'matrix-based PT'. It requires a list of PT stops and matrices with information about travel times and/or distances between these stops. For more information, see `http://matsim.org/extensions/matrixbasedptrouter`.

[7] This approach is based on the (informally stated) goal of the Berlin public transport company to generally achieve door-to-door travel times that are no longer than twice as long as car travel times. This, in turn, is based on the observation that non-captive travelers can be recruited into PT when it is faster than this benchmark (Reinhold, 2006).

cases, all other modes than car are assumed to run continuously and without capacity restrictions (Grether et al., 2009a; Rieser et al., 2009). In recent publications, there have been very successful attempts to model public transport in a much more sophisticated way within the MATSim framework (see, e.g., Erath et al., 2012; Neumann et al., 2014; Rieser, 2010). However, the focus of this thesis is rather on behavioral modeling and economic evaluation of transport policies than the improvement of detailed modeling techniques. As long as elasticities of demand between the different modes are in a valid range, the rather simple approach presented above seems to be sufficient in order to capture user reactions to policy changes. Clearly, policies, that have local effects on the transport supply of other modes, can not be investigated.

The execution of plans provides output describing what happened to each individual agent during the execution of its plan by so-called *events*. These events capture incidents in the simulated world, e.g. when an agent enters or leaves a road segment, starts or ends an activity, pays a toll, etc. In principle, the framework allows for the definition of arbitrary events that can be defined by the user (for an example, see later in Sec. 2.2.2). An event is simply characterized by an exact time and by an event type. Additionally, attributes can be defined that describe the event more precisely, e.g. agent ID, location, etc. It is therefore straightforward to grab very detailed information during the simulation and to calculate indicators such as travel times or generalized costs per link, trip travel times, trip lengths, percentage of congestion, and many more.

2.2.1.3 Evaluating Plans (Scoring)

In order to compare plans in a choice model, it is necessary to assign a quantitative measure (or score[8]) to the performance of each plan. In this thesis, an utility-based approach is used. The total utility $V_{p,j}$ of a plan p for individual j is computed by

$$V_{p,j} = \sum_{i=1}^{n} \left(V_{perf,i} + V_{tr,i} + V_{late,i} \right) . \tag{2.1}$$

The total utility is computed after execution in units of utility (utils). In Eq. 2.1, n is the total number of activities in plan p; $V_{perf,i}$ is the (positive)

[8] Note that 'score' is the technical term in most MATSim-related publications. 'Utility' is the common expression in economics and is therefore used in this thesis. Both terms refer to the same absolute value.

utility earned for performing activity i; $V_{tr,i}$ is the (negative) utility earned for traveling during trip i; and $V_{late,i}$ is the (negative) utility earned for arriving late to activity i.[9] Activities are assumed to wrap around the 24-hours-period, that is, the first and the last activity are stitched together. In consequence, there are as many trips between activities as there are activities.

The following empirically determined specifications of the different contributions to Eq. 2.1 have proven to be useful:

- A logarithmic form is used for the positive utility earned by performing an activity (Charypar and Nagel, 2005):

$$V_{perf,i}(t_{perf,i}) = \beta_{perf} \cdot t_{*,i} \cdot \ln\left(\frac{t_{perf,i}}{t_{0,i}}\right) , \tag{2.2}$$

  where t_{perf} is the actual performed duration of the activity, t_* is the 'typical' duration of an activity, and β_{perf} is the marginal utility of an activity at its typical duration. β_{perf} is the same for all activities, since in equilibrium all activities at their typical duration need to have the same marginal utility. $t_{0,i}$ is a scaling parameter that is related both to the minimum duration and to the importance of an activity. As long as dropping activities from the plan is not allowed, $t_{0,i}$ essentially has no effect.

- In this thesis, the disutility of traveling is derived from mode choice survey data. In all Case Studies, travel time and monetary costs are considered as attributes of every car and PT trip. In consequence, the travel related part of utility is defined by the following functional form:

$$\begin{aligned} V_{car,i} &= \beta_{tr,car} \cdot t_{i,car} + \beta_c \cdot c_{i,car} \\ V_{pt,i} &= \beta_0 + \beta_{tr,pt} \cdot t_{i,pt} + \beta_c \cdot c_{i,pt} , \end{aligned} \tag{2.3}$$

  where t_i is the travel time of a trip to activity i, and c_i is the corresponding monetary cost. Travel times and monetary costs are in the simulation dependent on every choice dimension (e.g. route, mode, time). The *beta* parameters depict the preferences of the

[9] Note that $V_{late,i}$ is only used in Case Study I in Sec. 3.3. This is due to the fact that in real-world scenarios, agents can have more than one work activity, e.g. one in the morning and one in the afternoon. In such a case it is complicated to specify whether an agent starts the activity late or not.

individual: β_0 an a-priori preference for one of the transport modes that depends on the sign of this parameter (see later in Sec. 2.3.2); β_{tr} the perception of travel time; and β_c the perception of monetary costs. In real-world observations, these parameters are typically found to vary across individuals, trip purposes, etc. In Ch. 3 of the thesis, β_c will be varied according to the individual's income.

- The disutility of being late is, for Case Study I only, defined by:

$$V_{late,i}(t_{late,i}) = \beta_{late} \cdot t_{late,i} \ , \tag{2.4}$$

where β_{late} is the marginal utility for being late, and $t_{late,i}$ is the time being late to activity i. $t_{late,i}$ is calculated by subtracting the latest start time from the actual start time of activity i. For activities where no latest start time is defined, no late penalty will apply.

In principle, waiting times resulting from early arrival could also be punished. Early arrival means that an agent arrives at an activity location earlier than the opening time. There is, however, no immediate need to punish early arrival, since waiting times are already indirectly punished by foregoing the reward that could be accumulated by doing an activity instead. In economics, this costs of foregoing the reward of one alternative because of choosing another alternative out of mutually exclusive options, is called opportunity cost (von Wieser, 1927; Williamson, 1993). In the context of activity scheduling decisions, foregoing one time unit of performing an activity is then called marginal *opportunity cost of time* or marginal *utility of time as a resource* (Börjesson and Eliasson, 2014; DeSerpa, 1971; Jara-Díaz, 2003). Unfortunately, estimating this opportunity cost of time β_{perf} and the additional (dis)utility from traveling β_{tr} separately from survey data is methodologically complex. Additionally, the survey needs to be explicitly designed in a way to allow for this separate estimation (Jara-Díaz et al., 2008), and can therefore not be done with all survey data (see later in Sec. 3.2.2). Assuming there is a separate value for the opportunity costs of time available, the effective disutility of waiting is already $-\beta_{perf} \cdot t_{*,i}/t_{perf,i} \approx -\beta_{perf}$. Similarly, that opportunity cost incurs when traveling. No opportunity cost needs to be added to late arrivals, because the late arrival time is spent somewhere else. In consequence, the effective disutility of arriving late remains, wherever applicable, at β_{late}.

2.2.1.4 Learning (Re-planning)

Plan Mutation A plan can be modified by various *modules*. Typically, there is one module for every available choice dimension. These modules are customizable, they can independently be switched on and off, or be replaced by other implementations. At the beginning of an iteration, every re-planning module modifies for a certain share of agents a copy of one of their existing plans: this percentage of agents is referred to as module-specific 're-planning rate'. That is, these agents are forced to try out new options that are then—after execution—evaluated by their utility function.[10] In this thesis, three choice dimensions are considered in which agents can react to policy changes: route choice, mode choice, and time choice. Not every Case Study uses all choice dimensions, and the implementations also differ; details for every Case Study are given in the corresponding sections. In the following, an overview about all modules and their implementations is presented:

1. *Route Choice Module (RCM)*: The route choice module is a time-dependent best path algorithm, which uses time-of-day-dependent generalized costs (or disutility of traveling) for every link. At the beginning of every iteration and according to the re-planning rate of the module, it proposes new routes to a certain share of agents. It bases its decision for new routes on the output of the car traffic flow simulation and the knowledge of congestion in the network: Attributes of new routes—travel time and (possibly agent-specific) monetary costs—are taken from the previous iteration, using feedback from the multi-agent simulation structure. Travel times are, for performance reasons, provided as average values in 15 *min* time bins. For the calculation of generalized costs, they are valued with the (possibly mode-, and agent-specific) perception of these attributes β_{tr} and β_c, which are also used in the evaluation of plans.

2. *Mode Choice Module (MCM)*: Two different implementations of the mode choice module are used in this thesis:

   a) A plan only allows for one single transport mode (car or public transport). In this case, mode choice is modeled by making sure

[10] The re-planning rate needs to be defined carefully: Forcing too many agents on new options might result in unstable results, e.g. oscillating traffic patterns from iteration to iteration. Forcing a too small number of agents on new options might result in slow convergence when trying to find a Stochastic User Equilibrium (SUE).

that every agent has at least one car and at least one public transport plan (Grether et al., 2009a; Rieser et al., 2009).

b) A plan allows for different transport modes. In this case, mode choice is modeled by an implementation that changes the transport mode of a car sub-tour to public transport or from a public transport sub-tour to car. A sub-tour is defined as a sequence of trips between activity locations. However, the simulation makes sure that a car can only be used if it is parked at the current activity location. Thus, a sub-tour is defined as a sequence of trips where the transport mode can be changed while still being consistent with the rest of the trips: For instance, it is assured that a car which is used to travel from home to work in the morning needs to be back at the home location in the evening. Or, if an agent decides to go for lunch by car, then the car needs to be available at the work location and the whole sub-tour of traveling to lunch and back to work needs to be changed to car.

3. *Time Choice Module (TCM)*: This module is called to change the duration of activities in an agent's plan. After picking the activity, the approach applies a random mutation to the duration attribute (Balmer et al., 2005). The time range in which durations are mutated can be configured.

Plan Selection All agents who are not forced on a new option by any of the above modules select one of their existing plans. The probability to change from the selected plan to a randomly chosen plan of the choice set follows Nagel and Flötteröd (2012) and is calculated by:

$$p_{change} = min\left(1, \alpha \cdot e^{\frac{\mu \cdot (V_{random} - V_{selected})}{2}}\right) , \tag{2.5}$$

where α is the probability to change if both plans have the same utility, set to 1%; μ is a sensitivity parameter that captures the variance of the difference between the random components of utility $\epsilon_{random} - \epsilon_{selected}$;[11] and $V_{random,selected}$ is the utility of the random/selected plan after the last

[11] For more information concerning the interpretation and influence of μ within the MATSim framework, please refer to Raney and Nagel (2006), or see Sec. 2.3. For potential conceptual improvements, please refer to Nagel and Flötteröd (2012).

execution (see Sec. 2.2.1.3). In steady state, this model reproduces the same choice probabilities as a standard Multinomial Logit (MNL) model.[12]

The repetition of the iteration cycle in Fig. 2.1 coupled with the agent database enables the agents to improve their plans over many iterations. The iteration cycle continues until the system has reached a relaxed state. At this point, there is no quantitative measure of when the system is relaxed; the cycle is just allowed to continue until the outcome is stable.

2.2.2 Emission Modeling Tool

This section aims at presenting the emission modeling tool that is used for emission calculation in Ch. 4 and Ch. 5. The tool has been developed and tested by Hülsmann et al. (2011) and further improved by Kickhöfer et al. (2013). It essentially calculates warm and cold-start exhaust emissions for private cars and freight vehicles by linking MATSim simulation output to the detailed database of the Handbook on Emission Factors for Road Transport (HBEFA), which is available for many European countries. The upcoming sections are structured as follows: Sec. 2.2.2.1 reviews other attempts in the literature to model transport related emissions. Sec. 2.2.2.2 presents an overview of the Emission Modeling Tool (EMT) that is developed as part of this thesis. That section is an edited version of the description in Kickhöfer et al. (2013). Finally, Sec. 2.2.2.3 shows how the tool is embedded in the software structure of MATSim.

2.2.2.1 Integrated Approaches for Modeling Transport and Emissions

Over the last two decades, modeling transport related environmental externalities has gained more and more attention in transportation science. For this reason, the following paragraphs shortly present some recent attempts in the area of exhaust emission modeling; additionally, they highlight differences to the EMT which will then be described in the subsequent sections.

Creutzig and He (2009) and Michiels et al. (2012) use very aggregated figures to estimate air pollution in Beijing and whole of Belgium, respectively. Both approaches do not mention any particular underlying transport model. It seems that transport related emissions are based on aggregated origin-destination matrices or aggregated demand functions. These two studies

[12] For a detailed description of the relationship between the MATSim choice model and Discrete Choice Theory, please see Sec. 2.3.1.

are on a very different level of aggregation than the EMT in this thesis, and a comparison does not seem very useful.

Beckx et al. (2009) use a sophisticated activity-based model to simulate activity schedules for roughly 30% of all households in the Netherlands. Traffic assignment for passenger cars is performed by using an aggregated 'all-or-nothing' assignment approach, resulting in hourly aggregated traffic flows on the network. Based on the average speed for a trip, the macroscopic emission model MIMOSA then calculates emission and fuel consumption rates, possibly dependent on vehicle category. The idea of using an activity-based model to simulate time-dependent emissions is similar to the EMT. In contrast to the latter, the underlying transport in Beckx et al. (2009) does not account for congestion effects and different traffic states. Additionally, similar macroscopic emission models are typically unable to capture some of the microscopic behavior accurately (see, e.g., Ahn and Rakha, 2008).

Hirschmann et al. (2010) link the microscopic traffic flow simulator VISSIM with the instantaneous emission model PHEM[13]. At a first glance, this approach seems very promising, as it also builds the basis for the HBEFA database. In contrast to the EMT, it is not suitable for large-scale scenarios due to the computational complexity of VISSIM. In Kraschl-Hirschmann et al. (2011), the same authors attempt to develop a parametrization of fuel consumption based on average speeds of vehicles. Such parametrization could in the future be helpful to replace time-consuming lookups in large databases (e.g. HBEFA). However, the model would need to allow for more input variables (e.g. vehicle category, traffic state, etc.) and to provide more differentiated outputs such as different emission types.

In a similar study, Song et al. (2012) couple VISSIM with the emission modeling tool MOVES. They find that the VISSIM-simulated vehicle-specific power distribution for passenger cars deviates significantly from the observed distribution. In consequence, the estimated emissions also contain significant errors. Here again, the proposed model can not be used for large-scale scenarios for the same reason as above. Additionally, it seems questionable whether such detailed modeling will become superior to less detailed models such as the EMT in this thesis.

Wismans et al. (2013) compare passenger car emission estimates of static and dynamic traffic assignment models. They claim that little research has been done in connecting macroscopic or mesoscopic dynamic traffic

[13] The model uses speed trajectories as input and was tested against the emission modeling tool of this thesis in a paper by Hülsmann et al. (2011).

assignment models with emission models. According to the authors, static assignment models predict congestion on the wrong locations and ignore spillback effects. They argue that emission hotspots are, in consequence, also predicted at the wrong locations and/or with the wrong amplitude. Therefore, they couple a static and a dynamic traffic assignment model with the exhaust emission model ARTEMIS. Large differences in air pollutant emissions are found, and hotspot locations differ.

Hatzopoulou and Miller (2010) develop a methodology for calculating exhaust emissions, using MATSim as mesoscopic transport model. The approach is therefore fairly similar to the EMT of this thesis. In contrast to that study, the EMT does not assume fixed exhaust emissions per time unit. It uses a more detailed calculation of emissions based on the two different traffic states 'free flow' and 'stop&go'. It is, thus, able to capture congestion effects that emerge additionally to the time spent in traffic jam. Furthermore, the EMT calculates exhaust emissions for passenger cars *and* for trucks. Finally, since the methodology is based on HBEFA, it can be transfered to any scenario in Europe.

2.2.2.2 Emission Calculation

There are several sources of air pollution that can be assigned to road traffic: Warm emissions are emitted while driving and are independent of the engine's temperature. Cold-start emissions additionally occur during the warm-up phase and depend on the engine's temperature when the vehicle is started. Warm emissions differ with respect to *driving speed*, acceleration/deceleration, *stop duration*, road gradient, and *vehicle characteristics* that consist of vehicle type, fuel type, cubic capacity, and European Emission Standard Class (André and Rapone, 2009). Cold emissions differ with respect to *driving speed*, *distance traveled*, *parking time*, ambient temperature, and *vehicle characteristics* (Weilenmann et al., 2009).

As of now, the emission modeling considers all differentiations from above that are marked in *italic*. Road gradient and ambient temperature are not considered. The gradient is always assumed to be 0%, and ambient temperatures are assumed to be HBEFA average. Additionally to warm and cold-start emissions, evaporation and air conditioning emissions also result from road traffic. As of now, the latter are not considered in the emission modeling tool, because of the small contribution to the overall emission level.

The calculation of warm emissions is composed of two steps:

1. Deriving *kinematic characteristics* from the simulation
2. Combining this information with vehicle characteristics in order to extract emission factors from the HBEFA database

In the first step, driving speed as well as stop duration (and possibly an approximation of acceleration/deceleration patterns) is captured by a mapping of MATSim's dynamic traffic flows to HBEFA traffic states. These traffic states, namely 'free flow', 'heavy', 'saturated', and 'stop&go', have been derived from typical driving cycles, i.e. time-velocity profiles. A parametrization of these profiles led to the definition of these traffic states, which depend on speed limit, average speed, and road type. Thus, typical emission factors for a certain traffic state on a certain road segment can be looked up in the HBEFA database. In MATSim, neither the location on a road segment nor the exact driving behavior of an agent is known (see Sec. 2.2.1). It is, however, rather straightforward to extract agent's travel times on the road segment which, thanks to the queuing model, also includes interactions with other agents and spillback effects. Therefore, the average speed of an agent on a certain road segment is used to identify the corresponding HBEFA traffic states, and to assign emission factors to the vehicle. As of now, the emission modeling tool only considers the two traffic states free flow and stop&go.[14] Each road segment is divided into two parts representing these two traffic states. The distance l_s that a car is driving in stop&go traffic state is determined by the following equation:

$$l_s = \frac{l\ v_s(v_f - v)}{v(v_f - v_s)}\ , \tag{2.6}$$

where l is the link length in km from the network, v_s is the stop&go speed in km/h for the HBEFA road type, v_f is the free flow speed in km/h from the network, and $v = \frac{l}{t}$ is the average speed on the link for the vehicle, t being the link travel time of the vehicle in the simulation. For the derivation of Eq. 2.6, please refer to Appendix A.1. The distance that the car is driving in free flow traffic state is then simply the remaining link length $l_f = l - l_s$. The interpretation of this approach is the following: Cars drive in free flow until they have to wait in a queue. Only in the queue, stop&go traffic state applies. According to the MATSim queue model presented in Sec. 2.2.1, a

[14] This simplification is due to the fact that the difference between the emission factors of the traffic states free flow, heavy, and saturated, are only marginal. In contrast to those traffic states, the emission factors for stop&go are roughly twice as high.

queue emerges if demand exceeds capacity of a road segment which can also result in spillback effects on upstream road segments. The length of the queue is, thus, approximated by Eq. 2.6, where the average speed v on a link is the only exogenous variable.

For the second step, agent-specific vehicle attributes are needed. They are usually obtained from survey data during the initial population synthesis. The vehicle attributes typically comprise vehicle type, age, cubic capacity and fuel type. As MATSim keeps socio-demographic information throughout the simulation process, it can be used at any time for the necessary lookup in the detailed HBEFA database. Additionally, the emission modeling tool is designed in such way that fleet averages are used, whenever no detailed vehicle information is available.

The calculation of cold-start emissions is again composed of two steps:

1. Deriving *parking duration* and *accumulated distance* from the simulation

2. Combining this information with vehicle characteristics in order to extract emission factors from the HBEFA database[15]

Parking duration refers to the time a vehicle is not moved *before* cold-start emissions are produced. It is calculated by subtracting an activity's start time from the same activity's end time and by checking if the trip to and from the activity is performed by car. Emission factors in HBEFA are differentiated by parking duration in one hour time steps from 1 h to 12 h. After 12 h, the vehicle is assumed to have fully cooled down. The accumulated distance refers to the distance a vehicle travels *after* the cold start. According to HBEFA, there are different cold-start emissions for short trips ($< 1\ km$), and longer trips ($\geq 1\ km$). In reality, cold-start emissions are emitted along the route after a cold start; the emission modeling tool, however, as of now maps all these emissions to the road segment where the engine is started. Overall, cold-start emission factors increase with parking duration and accumulated distance. Additionally, they depend on vehicle attributes. The lookup for this information is identical to the one described for warm emissions.

In order to further process the warm and cold-start emissions, so-called *emission events* are generated during the simulation in a separate events stream. The definition of emission events follows the MATSim framework

[15] Please note that HBEFA provides cold-start emission factors only for passenger cars. Freight traffic therefore only produces cold-start emissions of passenger cars.

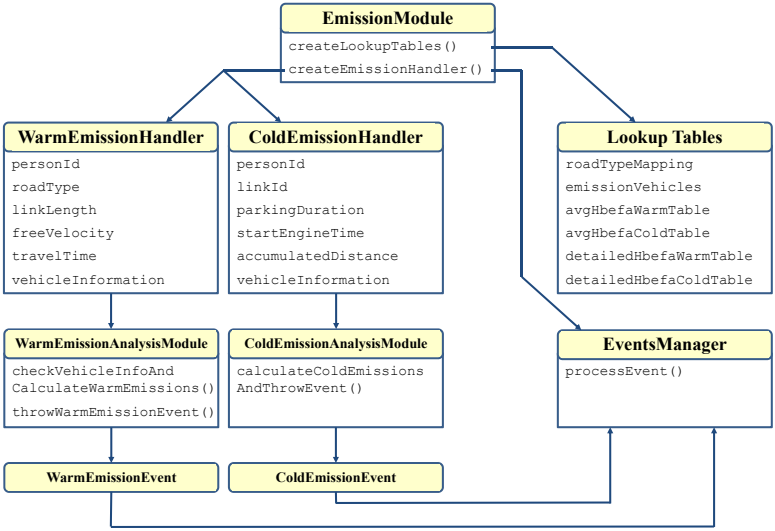


Figure 2.2: Software structure of the emission modeling tool.

that uses events for storing disaggregated information in XML format. The following section will now provide more information on the software structure of the emission tool.

2.2.2.3 Software Structure

The information in this section refers to code that can be found in the MATSim repository.[16] In the following, the software structure of the emission modeling tool at revision 25560 is described. For information on how to use the tool, please refer to the `package-info.java` class in the corresponding package.

Fig. 2.2 shows the simplified software structure of the emission modeling tool. The core of the tool is the `EmissionModule` which needs to be created before the simulation starts. Additionally, there are two public methods that need to be called: `createLookupTables()` and `createEmissionHandler()`. The former creates lookup tables from text files that have been exported from the HBEFA database. The path to these text files can be configured in the

[16] The exact location at the time of writing is `https://svn.code.sf.net/p/matsim/source/playgrounds/trunk/vsp/src/main/java/playground/vsp/emissions/`.

`VspExperimental` config group. Mandatory inputs are files for the creation of `roadTypeMapping`, `emissionVehicles`, and `avgHbefaWarm/ColdTable`. The first lookup table maps road types from the MATSim network to HBEFA road types. For this mapping, it is necessary to classify the network road types into HBEFA categories; this requires some transport engineering knowledge. The second lookup table defines the vehicle attributes of every person in the population. It should therefore be generated during the population synthesis process. If no detailed information is available, the vehicle lookup table still needs to specify whether the vehicle is a car or a truck. The current implementation uses the MATSim vehicle interface `Vehicles` as container for storing the relevant data in `VehicleType`.[17] The last two mandatory lookup tables provide warm and cold emission factors in g/km, respectively. The data is stored using a unique key. For the construction of this key, information from the two tables above is needed as well as information derived from the simulation as described in Sec. 2.2.2.2. The latter information is depicted in Fig. 2.2 as variables of the two classes `WarmEmissionHandler` and `ColdEmissionHandler`. These two handlers implement several MATSim `EventHandler` interfaces in order to extract the necessary information from the simulation. After gathering this information, the `WarmEmissionHandler` asks its `WarmEmissionAnalysisModule` to reconstruct the key and look up the emission factors in the respective table. Similarly, the `ColdEmissionHandler` asks the `ColdEmissionAnalysisModule`. These analysis modules then create `Warm/ColdEmissionEvents` which follow the MATSim `Event` interface definition. Finally, the resulting events stream is written in a joint emission events file by a separate `EventsManager`.

For the calculation of emissions that depend on agent-specific vehicle characteristics, the emission vehicle file must contain this specific information, the corresponding flag in the `VspExperimental` config group needs to be switched on, and detailed emission factor tables additionally need to be exported from HBEFA and provided for the emission modeling tool.

2.3 Agent-based Economic Evaluation

Sec. 2.1 presented theoretical and practical aspects of the BCA approach along with limitations and assumptions that often raise criticism. Sec. 2.2

[17] Please note that this information is *only* used for storing data on individual vehicle characteristics and other information in the emission vehicle file will be omitted by the simulation.

then focused on the behavioral modeling of individuals in a agent-based simulation, and showed how agent-specific time-dependent emissions can be computed. In order to bring these two aspects together, this section will explain how economic evaluation can be performed in an agent-based framework. As the thesis focuses on the valuation of positive and negative effects of mobility behavior for society, this section does not cover other crucial factors for BCA such as implementation and maintenance costs of transport policies.

The process of economic policy evaluation typically consists of two steps: First, forecasting the changes in the system as a reaction to the policy. Second, assigning some monetary value to these changes. As will be shown in the next sections, these two steps are neither completely independent nor completely dependent on each other.

2.3.1 Describing Human Behavior

Estimating benefits of a policy intervention relies on a sound descriptive model that is capable to predict the resulting behavioral changes of individuals. Historically, *aggregated elasticities* are probably the most popular concept that is used for behavioral forecasting in transport planning (see, e.g., de Jong and Gunn, 2001; Graham and Glaister, 2002; Parry and Small, 2005). In the simplest case, elasticities describe the change of travel demand as reaction to a monetary price change for the whole market, always relative to the status quo. Assuming an initial price level of p_0, a final price level of p_1, an initial travel demand q_0, and a final travel demand of q_1, the price elasticity of demand is defined by:

$$\eta_{q,p} = \frac{\frac{q_1 - q_0}{q_0}}{\frac{p_1 - p_0}{p_0}} \tag{2.7}$$

That is, a relative change in the price level by 1% is predicted to lead to change in travel demand of $\eta_{q,p}$%. The congeniality of elasticities is that they can relatively easily be obtained from market observations, i.e. from measuring a change in quantities for a known price change. Instead of price changes, also changes in travel times or other behaviorally relevant parameters can be used, resulting, e.g., in travel time elasticity of demand. However, the values strongly depend on the particular circumstances of the measurement. Additionally, the measurement might be biased by changes in the system that occur parallel to the price/time changes. There are

many studies in the literature to determine price elasticities or travel time elasticities for mode choice, departure time choice, destination choice, travel frequency, car ownership, and activity location choice (for an extensive literature review see, e.g., de Jong and Gunn, 2001). The attempt of obtaining more and more disaggregated values for single origin-destination relations, different trip purposes, income groups, etc., makes the observation very difficult, and technically leads to the estimation of individual elasticities for every person under consideration.

For this reason, the use of aggregated elasticities is rather inconvenient in the context of agent-based modeling where the focus is on the individual's decision making. These models therefore use Discrete Choice Theory in order to describe and predict human mobility behavior. This theory goes back to work by Luce and Suppes (1965) and McFadden (1975). Two standard textbooks in this area are Ben-Akiva and Lerman (1985) and Train (2003). Discrete choice models are typically used to describe individual choices among *mutually exclusive* alternatives. In order to apply this theory, two additional preconditions need to be met (Train, 2003, p.16): First, *all* relevant alternatives need to be known and described by the relevant preferences of the individual, and by the relevant attributes of the alternative. Second, the number of alternatives needs to be finite.

Preferences of individuals can be estimated based on survey data, which consists of different observations of individual choices. For an application using maximum-likelihood estimation, see later in Ch. 3. However, the estimated parameters typically do not reproduce all individual choices correctly, or—in other words—individuals do not always choose the alternative with the highest utility according to their supposed utility functions; this observation violates the assumption about the consistency and transitivity of preferences. For this reason, there was a strong need for methodological improvement. Luce and Suppes (1965) distinguished between two possible interpretations of this observed choice behavior: Either, people chose randomly among their alternatives (Constant Utility Model). Or, the choice only *appears* to be random, since the observer does not include all relevant decision variables in the model. Since the latter interpretation is still in line with the necessary assumptions on consistency and transitivity of preferences, McFadden (1975) built his RUM by introducing a *random component* to the utility formulation. This thesis follows the approach by defining utility as:

$$U_p = V_p + \epsilon_p \ , \tag{2.8}$$

where U_p is the true utility of the alternative p, which corresponds in this thesis to an individual's daily plan (see Sec. 2.2.1.4); V_p is the observed or systematic part of utility described by the utility function (see Eq. 2.1); and ϵ_p is the random component of utility. As a result, the random component allows for choices that are—according to the systematic parts of utility calculated by the utility functions—*irrational*. In consequence, there is a *probability* to select the option with the highest V_p, as well as (lower) probabilities to select the other options with lower V_p. Assuming that all ϵ_p are independent and identically distributed (i.i.d.) following a Gumbel distribution, this leads to a MNL model with the choice probability p_p for plan p:

$$p_p = \frac{e^{\mu \cdot V_p}}{\sum_P e^{\mu \cdot V_P}} \ , \tag{2.9}$$

where P is the total number of plans in the choice set, and μ is related to the variance of the random component. From the modeler's perspective, μ describes how rational decision makers behave, given a difference in the systematic part between utilities of alternatives. To give an example on the influence of μ on the choice probabilities of $P = 2$ alternatives a and b with $V_b > V_a$: following Eq. 2.9, the corresponding choice probabilities are defined by

$$p_a = \frac{1}{1 + e^{\mu(V_b - V_a)}} \qquad p_b = \frac{1}{1 + e^{\mu(V_a - V_b)}} \qquad .$$

As one can see, the choice probabilities only depend on the difference between the systematic parts of utility $V_a - V_b$[18], and on the parameter μ. For $\mu \to 0$, this results in a completely random choice behavior and choice probabilities of $p_a = p_b = \frac{1}{2}$. For $\mu \to \infty$, this results in a completely rational behavior and choice probabilities of $p_a = 0$ and $p_b = 1$. The first case corresponds to a very large variance, the latter to a very small variance of the difference between the random components $\epsilon_b - \epsilon_a$. In steady state, the MATSim choice model is in principle equivalent to the standard MNL model (Nagel and Flötteröd, 2012).

However, this equivalence is only valid if agents can choose from a valid choice set. If MATSim is used as a choice set generator in the iterative loop of Fig. 2.1, there exist three methodological issues at the time of writing:

[18] It can therefore be argued that with the use of Discrete Choice Theory, one has already left the ground of an ordinal scale of utility, since the difference in utility influences the choice probabilities.

First, the maximum number of plans P in the choice set of every agent is limited by memory constraints. When a new plan is added to a person that already reached the maximum number of plans permitted, the plan with the lowest utility is deleted. That is, the choice set might not be complete. Second, plans might be correlated. This is very likely if they are mutated by best-response re-planning modules (e.g. the route choice module); but also random mutations might result in correlated plans. That violates the required IIA (Independence of Irrelevant Alternatives) property of the choice set that is needed for a MNL model. Third, the current MATSim implementation has a tendency to keep similar and thus correlated plans when the number of plans has grown beyond P. These three issues might lead to biased behavior, and also have consequences for economic evaluation. A discussion on these aspects, as well as a presentation of possible solutions will be given in the next section.

Overall, it is important to note that the simulation of individual choice behavior can again be used to calculate any desired aggregated elasticity, e.g. for different subpopulations. This nice property will be used in Ch. 4 for determining aggregated price elasticities of car travel demand and of emissions.

2.3.2 Valuing Human Behavior on Individual Level

Following de Jong et al. (2007), a major advantage of the agent-based approach is that it allows for a seamless integration (i) of forecasting behavioral changes as a reaction to changes in the system, and (ii) of the subsequent economic evaluation. In this section, it is shown how agent-specific preferences which determine behavior can directly be used for deriving individual VTTS, or for obtaining the individual utility differences resulting from a policy. The upcoming Sec. 2.3.3 will then focus on how these individual utility changes can be used in order to derive some indicator of overall welfare change for the population under consideration.

For illustration purposes, look again at the travel related part of utility in this thesis from Eq. 2.3:

$$\begin{aligned} V_{car,i} &= \beta_{tr,car} \cdot t_{i,car} + \beta_c \cdot c_{i,car} \\ V_{pt,i} &= \beta_0 + \beta_{tr,pt} \cdot t_{i,pt} + \beta_c \cdot c_{i,pt} \ . \end{aligned}$$

As explained before, β_0 is the mode-specific Alternative Specific Constant (ASC) of the estimated MNL model. It indicates for $\beta_0 > 0$ an a-priori

preference for public transport, and for $\beta_0 < 0$ an a-priori preference for car. The estimated constant might catch the net effect of some unobserved attributes that are not considered in the systematic part of utility $V_{car,pt}$, e.g. the trade-off between access/egress times in public transport and the time spent for finding a parking spot when traveling by car. β_{tr} is defined as the marginal utility of travel time, β_c as the marginal utility of monetary costs. These parameters capture the preferences of individuals in the trade-off between travel time and monetary costs of trips; both are typically found to be mode dependent which results in *mode-dependent* VTTS. They describe the willingness-to-pay for reducing the travel time by one time unit. The VTTS in general is calculated as follows:

$$VTTS = \frac{\frac{\partial V}{\partial t}}{\frac{\partial V}{\partial c}} \tag{2.10}$$

With regard to the utility functions in Eq. 2.2 and Eq. 2.3 and with the argument concerning the opportunity costs of time from Sec. 2.2.1.4, the VTTS can be calculated by dividing the effective marginal utility of travel time $\beta_{tr_{eff}}$ by the marginal utility of monetary costs β_c, where $\beta_{tr_{eff}} = -\beta_{perf} \cdot t_{*,i}/t_{perf,i} + \beta_{tr} \approx -\beta_{perf} + \beta_{tr}$. They are, thus, defined in units of money per time unit.

Additionally to the mode dependency of β_{tr} and β_c, the parameters may vary across individuals j, trip purposes i, etc. When investigating the influence of individual income on cost perception in Ch. 3, the marginal utility of money defined by $-\beta_c$ is income-dependent. In consequence, the resulting VTTS are additionally *income-dependent*.

In contrast to many conventional transport simulation tools that use monetary costs as units of the generalized cost function, utility calculation in this thesis is performed in units of utility. That is, VTTS are not explicitly but implicitly contained in the utility function. In consequence, the utility level of every agent before the policy can be compared to her utility level after the policy. The question arises whether

- the utilities of the executed plans, or
- the utilities of the choice set (logsum term)

should be used for economic evaluation. In the literature, the second option has been proposed for applied welfare analysis with Discrete Choice Models (de Jong et al., 2006, 2007; Small and Rosen, 1981). In principal, the logsum

term represents the Expected Maximum Utility (EMU) for a user that has several options $p = 1..P$ in her choice set. It values the utility of the best option, but the existence of alternatives is additionally valued (see Appendix A.3, where an alternative formulation of the logsum term highlights this characteristic). For the calculation, a complete choice set for that user, the systemic part of utility for every option V_p, and the variance of the unobserved attributes (or random components) $\frac{1}{\mu}$ in the RUM need to be known. For the calculation of the individual utility level in units of utility, the logsum term is defined as follows:

$$logsum = EMU = \frac{1}{\mu} \cdot ln \sum_{p=1}^{P} e^{\mu V_p} \tag{2.11}$$

This formulation is used in Ch. 5 for welfare calculations. However, as described in the previous Sec. 2.3.1, the use of MATSim as choice set generator yields issues with impacts for the economic evaluation: incompleteness of the choice set and correlation of daily plans. In the plans innovation process of the simulation, the plan with the lowest utility is removed whenever the maximum number of plans are reached for an agent. In consequence, this decreases the probability that heterogeneous plans survive and increases the probability of very similar plans. This, again, increases the likelihood that the final choice set is correlated, i.e. containing only plans that are very similar to the best plan (see Prato, 2009, for a review on correlation of routes).[19] For these reasons, Ch. 3 uses the utilities from executed plans for welfare calculations. This partly circumvents the problem of correlation between alternatives for evaluation, but has substantially less theoretical foundations. Additionally, the modeled behavior might still be biased.

The upper boundary of the error when using the logsum term for evaluation of correlated choice sets can be approximated as follows: Assume that all plans $p = 1..P$ in the choice set of a person are completely correlated (e.g. only copies of the best plan with utility $\tilde{V}$). Following Eq. A.11, the

[19] A possible solution to this problem is most likely composed of two steps: First, more heterogeneity needs to be introduced into the choice set generation, e.g. by producing very different plans. Second, the method for plans removal needs to be based on a MNL model where the difference in utility enters, similar to the approach of selecting plans for execution. This could be done by an implementation of a method called 'pathsize logit' which uses similarity measures for plans (see Ben-Akiva and Bierlaire, 1999; Frejinger and Bierlaire, 2007, for a possible solution in route choice).

maximum error E_{max} with complete correlation of plans and with $\mu = 1$ is:

$$E_{max} = \left(\tilde{V} + ln \sum_{p=1}^{P} e^{\left(V_p - \tilde{V}\right)} \right) - \tilde{V} = ln \sum_{p=1}^{P} e^{0} = ln(P) \tag{2.12}$$

That means, in case of total correlation between plans, all utilities are overestimated by $ln(P)$, i.e. the error scales with the maximum number of plans.

To give recommendations to other researchers: the bias in choice set generation of MATSim needs to be fixed in the near future in order to obtain valid choice sets. This requires (i) the generation of more heterogeneous plans (see, e.g., Moyo Oliveros, 2013; Nagel et al., 2014, for such attempts in the PT and in the car mode, respectively); and (ii) the implementation of a pathsize logit model in the plans removal process (see, e.g., Grether, 2014). Having obtained these valid choice sets (Nagel and Flötteröd, 2012), the calculation of user benefits based on the logsum formulation is preferable. Using the logsum formulation with correlated choice sets requires a careful interpretation of the results. However, when looking at differences between the two states before and after a policy, this issue is unlikely to change results structurally: if the correlation remains roughly the same between the two states, the error of utility differences is small. If the correlation structure of plans changes, the error will—among other model specifications—depend on the number of iterations. In that sense, one could include some approximation of the error into the analysis of results, possibly similar to Eq. 2.12. If the differences in utility levels between the two states are in the same magnitude as $\ln(P)$, it is possible that the signal of the policy effect is smaller than the noise of randomness.

To sum up, it can be stated that agent-specific preferences will determine mobility behavior in the simulation. Additionally, the calculated individual utility differences, that result from a change in the system, can be directly used in order to identify winners and losers. Some economists claim that the modeler's task of providing information for decision support ends at this point (Ahlheim and Rose, 1989). However, as presented in Sec. 2.1.1, BCA requires some monetary valuation of the resulting behavioral changes. The next section will therefore review different possibilities to monetize and aggregate individual utility differences.

2.3.3 Aggregating Individual Values

Having obtained the individual changes in terms of utility by either applying Eq. 2.11 to every person, or by calculating the utilities of the executed plans, both before and after the policy, it seems to be necessary to convert these utility changes into monetary terms for economic evaluation. Unfortunately, there exists no 'correct' monetization or aggregation approach of individual utility differences, which is reflected by the ongoing discussion[20] between transport policy appraisal experts:

- The first stream argues in favor of a consistency between values used in demand modeling and appraisal (Grant-Muller et al. (2001, p.255), Bickel et al. (2006, p.S4 and p.S8), and Proost[21]). Values from the literature should only be used if values from the behavioral model are not available. They are, however, aware that this potentially limits the comparability of projects in different regions of the same state, or in different member states of the EU. According to these authors, additional indicators such as absolute time savings per income group should additionally be reported in order to address equity issues.

- In contrast to the above, Mackie and Worlsley (2013, p.12) state, that in the United Kingdom, "standard [VTTS] values per minute would be used across incomes, modes and regions. Therefore, practice is to use behavioural information for modelling but standard values for appraisal."

- Fowkes (2010), OECD (2006), and Gühnemann[22] argue slightly differently but into the same direction as Mackie and Worlsley (2013): modeling and evaluation should be based on the best heterogeneous preferences that are available; in the evaluation, additional weights should be introduced, e.g. to counter the effect of decreasing marginal utilities of money, or increasing VTTS with income, respectively. These weights would, thus, define the underlying equity concept of the appraisal method.

- However, as Ahlheim and Rose (1989) point out, there exists no approach to empirically determine these weights without assuming some

[20] A similar overview on this discussion is given by Börjesson and Eliasson (2014).
[21] S. Proost, personal communication.
[22] A. Gühnemann, personal communication.

arbitrary a-priori specification. In consequence, every interpersonal comparison of utility changes requires some normative decision, and the weights need therefore to be determined on a political level.

One goal of this thesis is to show the impacts of a possible integration between behavioral modeling and economic evaluation in the same agent-based framework while assuming heterogeneous user preferences. Since the additional weights from above can empirically not be determined, the approach implies a consistency between the values used in demand modeling and the values used in appraisal. Due to the fact that interpersonal comparisons of utility levels should be avoided, the following sections present two possibilities to monetize and aggregate the individual utility changes obtained from the behavioral model: First, a conversion of utility differences into *income equivalents*, and second, a conversion into *time equivalents* (possibly followed by some conversion into money terms). As will be shown in Ch. 3, the choice of the monetization and aggregation procedure can have major impacts on the results when heterogeneity is assumed in user preferences. At any rate, the choice of the procedure depends on (normative) decision whether one *EUR* or one h should be valued equally across individuals. It is therefore important that decision makers and modelers who deal with economic evaluation understand the possible effects of that choice; simply going with the most common approach may not be advisable.

2.3.3.1 Income Equivalents

The most common approach in welfare economics to convert utility changes into money terms is to calculate the monetary amount Δm_j that one would need to give or take from an individual in order to offset the impact of the policy on the utility level ΔV_j. This amount is equal to the willingness-to-pay/willingness-to-accept of the individual (Jara-Díaz, 2007; Small and Rosen, 1981). With respect to the utility function from Eq. 2.3, it is calculated to

$$\Delta m_j = -\left(\frac{\partial V_j}{\partial c}\right)^{-1} \cdot \Delta V_j \ , \tag{2.13}$$

where $-\left(\frac{\partial V_j}{\partial c}\right)^{-1} = -\frac{1}{\beta_c}$ is the inverse marginal utility of money. Please recall that this marginal utility of money might be person-specific, e.g. income-dependent (see later in Ch. 3). In this context, it is important to note that the formulation in Eq. 2.13 assumes that the conversion from

utility into willingness-to-pay/willingness-to-accept, respectively, can be based on the income from before the introduction of the policy. This implies that the marginal utility of money needs to be constant within the range of the price and/or quality change. In situations where individuals spend a rather important fraction of their available income on transportation, the issue is not so clear any more, and *income effects* need to be taken into account (Daly et al., 2008; Herriges and Kling, 1999; Jara-Díaz and Videla, 1989; Karlstrom and Morey, 2004). This is likely to be the case in developing countries. Since the present thesis only analyzes impacts of policies in industrialized countries, let it suffice to say that one would need to trace the effect of the interaction between costs and income in the simulation, and analyze how that affects Eq. 2.13.

The overall welfare change ΔW for the population with individuals $j = 1..J$ is then calculated by

$$\Delta W = \sum_{j=1}^{J} \Delta m_j \ . \tag{2.14}$$

As pointed out in Sec. 2.1.4, the above approach is often criticized for equity reasons: if the marginal utility of money is—in the behavioral model—assumed to decrease with income, and these values are directly (without additional weights) used in economic evaluation, rich people will have a stronger impact in the evaluation process than poor people. In turn, this might lead, e.g., to investments in expensive high-speed trains on major corridors rather than affordable train services for everyone. In terms of equity and public acceptance, such specification in the appraisal method might not be desirable. For this reason, the following section will present a different approach for aggregating and monetizing individual utility changes.

2.3.3.2 Time Equivalents

Another option to derive a monetary measure of welfare changes is composed of two steps: First, a conversion of individual utility changes into *equivalent hours of life time* (Jara-Díaz et al., 2008; Mackie et al., 2001). This would be the number of hours Δt_j that one would need to give or take from an individual in order to offset the impact of the policy on the utility level ΔV_j. Second, a monetization of the resulting numbers though an arbitrary conversion factor, i.e. the monetary value of one h for the

individual or for society.

In the MATSim sense, one could first calculate the corresponding time equivalent with respect to Eq. 2.2 and Eq. 2.3 by

$$\Delta t_j = \left(\frac{\partial V_j}{\partial t}\right)^{-1} \cdot \Delta V_j \ , \tag{2.15}$$

where $\left(\frac{\partial V_j}{\partial t}\right)^{-1}$ is the inverse marginal utility of time. This marginal utility of time might be person-specific in the sense that individuals pressed for time have a smaller t_{perf}, and therefore, their marginal utility of time

$$\frac{\partial V_{perf}}{\partial t_{perf}} = \frac{\partial \left(\beta_{perf} \cdot t_* \cdot \ln\left(\frac{t_{perf}}{t_0}\right)\right)}{\partial t_{perf}} = \beta_{perf} \frac{t_*}{t_{perf}} \tag{2.16}$$

is larger. The obtained time equivalents Δt_j could then be converted in monetary terms using the VTTS from Eq. 2.10 by applying

$$\Delta m_j = VTTS_j \cdot \Delta t_j \ . \tag{2.17}$$

For person-specific VTTS from the behavioral model, this would result in the same monetary amount as the income equivalent approach from Eq. 2.13. In contrast, following Mackie and Worlsley (2013), one could argue that one hour of life time of any individual is equally important for society, and, thus, use some average VTTS for monetization, e.g. $\overline{VTTS} = \frac{1}{J}\sum_{j=1}^{J} VTTS_j$. The overall welfare change ΔW for the population with individuals $j = 1..J$ is then calculated identically to Eq. 2.14.

2.3.3.3 Discussion

Income vs Time Equivalents The above sections showed how to monetize and aggregate individual utility differences via income equivalents or time equivalents, respectively, when assuming heterogeneity in user preferences. The following findings can be summarized:

- Income equivalents put emphasis on the individual willingness-to-pay, whereas time equivalents focus on time pressure which may be the same for a single mother as for a busy executive.

- The aggregation of income equivalents yields the overall willingness-to-pay of the population under consideration in order to realize a project. That is, one *EUR* is valued equally across individuals.

- The aggregation of time equivalents yields the overall equivalent hours of life time for the population under consideration that would be generated by the project. That is, one h of life time is valued equally across individuals.
- A monetization of time equivalents via person-specific VTTS leads to the same total benefit as directly aggregating income equivalents. This essentially offsets the equal value for one h of life time.
- A monetization of time equivalents via some average VTTS could therefore lead to a different total benefit than directly aggregating income equivalents. This maintains the equal value for one h of life time.

Heterogeneity of Preferences across Alternatives of the Same Individual
Both Sec. 2.3.3.1 and Sec. 2.3.3.2 showed monetization and aggregation rules where preferences vary across individuals. However, these preferences, and in consequence the VTTS, are often found to be additionally dependent on the transport mode, purpose of the expense, and purpose of the trip i (see, e.g., Börjesson et al., 2013; Jara-Díaz and Guevara, 2003; Mackie et al., 2001; Vrtic et al., 2008). If this finding should be included in the behavioral model, it obviously has consequences for the subsequent economic evaluation as the effective marginal utility of travel time and the effective marginal utility of money are in these cases potentially not uniform across all alternatives of the individual. To give an example: The parameter β_c from Eq. 2.3 can also be interpreted as the negative marginal utility of money, a conversion factor from monetary costs into units of utility. If this parameter was different between the two transport modes car and PT, one *EUR* spent for gasoline would influence the utility of that person differently than one *EUR* spent for a public transport ticket. In such cases, a simple conversion of utility differences of a person's whole daily plan into income equivalents via Eq. 2.13 would not be possible any more: it would be unclear which conversion factor to use. That is, with e.g. different β_c per transport mode, one could easily construct situations where utility levels rise or drop by a simple transfer of costs from one transport mode to another. The same problem arises if the effective marginal utility of travel time $\beta_{tr_{eff}}$ is different across alternatives of the same individual. However, there exist choice experiments where the marginal utility of time β_{perf} is estimated separately from the additional (dis)utility of traveling β_{tr} (see,

e.g., Jara-Díaz et al., 2008). Having obtained these parameters separately, it has been shown that the marginal utility of time can be used for calculating time equivalents (see Eq. 2.16). Analogically, income could be introduced as resource into the utility formulation of Eq. 2.1, similar to time as a resource (Eq. 2.2), i.e.

$$V_{inc,j}(y_j) = -\beta_c \cdot y_{*,j} \cdot ln\left(\frac{y_j}{y_{0,j}}\right) \ ,$$

where $-\beta_c$ is the marginal utility of money of the individual at the typical income $y_{*,j}$, y_j is the actual income of the individual, and $y_{0,j}$ is the minimum income of the individual. This would require choice experiments to separately estimate both summands of the *effective* marginal utility of money $\beta_{c_{eff}}$, i.e. the marginal marginal utility of money β_c and the additional (dis)utility of the expense $\beta_{c_{exe}}$ (e.g. specific for gasoline or ticket price). Then, β_c could be used for calculating income equivalents analogically to Eq. 2.16 However, all these detailed calculations would require to trace the agent's behavior in the simulation and directly convert the utilities depending on the transport mode, purpose of the expense, or purpose of the trip. For such attempt, more sophisticated infrastructure and careful testing of the software would be necessary, which is considered to be out of the scope of the present thesis.

Application in this Thesis For the monetization of individual utility differences via income equivalents, this thesis uses Eq. 2.13. Therefore, a uniform marginal utility of money across all alternatives of an individual is required. This can be achieved by forcing all cost related parameters of all alternatives to the same value in preference estimation.[23] However, choice modelers typically will not limit the model's degrees of freedom since it suppresses some information contained in the data.[24] It is therefore rather complicated to obtain the necessary parameter estimates from the literature. Where the raw data is available, the same model can be estimated with a uniform marginal utility of money across alternatives (Kickhöfer et al., 2011; Tirachini et al., 2014). As long as β_{tr} still comes out as mode dependent, the resulting VTTS remain mode dependent.

[23] This applies for Ch. 3 and Ch. 5, where an economic evaluation of policies is performed. Only in Ch. 4, different marginal utilities of money are considered. To the knowledge of the author, there is no best solution to this problem in the literature, the single value for the marginal utility of money is rather a necessary convention.

[24] J. de Dios Ortúzar, personal communication.

For the monetization of individual utility differences via time equivalents, this thesis builds the analysis on Eq. 2.15. However, as Eq. 2.16 indicates, the marginal utility of time might be different between individuals, trip purposes etc. Since a correct calculation of the inverse marginal utility of time would also require more sophisticated infrastructure, the presentation of the results will be based on the assumption that the actual duration of an activity t_{perf} is close to the typical duration of the activity t_*, and therefore $\left(\frac{\partial V}{\partial t}\right)^{-1} \approx \frac{1}{\beta_{perf}}$. This implicitly means that time pressure is not considered in the time equivalent numbers presented in this thesis. In consequence, the aggregation of time equivalents yields approximately the same results as an aggregation of units of utility, simply re-scaled by $\frac{1}{\beta_{perf}}$. Because of this approximation, the analysis will always present results in both, utils and time, even though an aggregation of utility over different individuals has no theoretical foundations.

Overall, the discussion in Sec. 2.3.3 showed that there exists some uncertainty whether the more and more disaggregated parameters from the behavioral model should be used in the subsequent economic evaluation. This emphasizes the advantages of a model that strictly distinguishes between these two steps. The model proposed in this thesis is therefore set up in such way. Additionally, the model is able to provide any desired additional decision indicator on any desired level of (dis)aggregation.

Chapter 3

Heterogeneity in User Preferences

3.1 Introduction

Policy measures in transportation planning aim at improving the system as a whole. In democratically organized societies, however, it might be rather difficult to realize policies when they have a negative impact on some part of the population, even if this is a minority—presumably, this has something to do with the fact that losses are weighed more than gains (Kahneman and Tversky, 1979). One controversial example for such policies is road user pricing, which has gained a lot of attention in the literature. From a theoretical perspective, it has been found that pricing schemes open up new possibilities to a more efficient allocation of limited road capacities in metropolitan areas, to a reduction of negative environmental effects, and to raising additional funds for publicly financed projects (e.g., Lindsey and Verhoef, 2000; Small, 1992; Vickrey, 1969, 1973). In this context, it has been discussed how to measure the welfare effects resulting from the policy and how the consideration of decreasing marginal utilities of money might influence the results (Bates, 2006; Herriges and Kling, 1999; Mackie et al., 2001; Small, 1983). Some studies indicate that pricing schemes tend to be regressive if no redistribution scheme is considered at the same time, and may so increase the inequality in welfare distribution (e.g., Franklin, 2006). Other authors state that the lack of public acceptance stems from the fact that individuals do not trust their government to reinvest the toll revenue in a meaningful way and therefore perceive the charge as an additional burden (Schade and Schlag, 2000).

However, the role of public acceptance has rarely been linked to the

individual welfare effects that result from policy measures. Furthermore, there is little literature on the public acceptance of non-pricing policies that might influence individual welfare levels in very different ways, and thus cause individuals to oppose it, e.g. for fairness reasons. One option to reach broader public acceptance for such policies may be to include a redistribution of toll revenues or a compensation of losers into the scheme.

Hence, methods and tools are needed that simulate welfare changes resulting from policies on a highly granulated level, e.g. considering each individual of the society. With such tools, policy makers are able to consider impacts of different proposed measures on the welfare distribution (OECD, 2006). In addition, it is possible to estimate the support level within the society and, if necessary, to evaluate alternatives for further discussion. For real-world scenarios, traditional transport planning tools using the four-step process combined with standard economic appraisal methods (e.g., Pearce and Nash, 1981) or studies using aggregated supply-demand functions with price elasticities (e.g., Bureau and Glachant, 2008; Creutzig and He, 2009) are not able to provide such analysis on the individual level. Additionally, they typically only consider one choice dimension, i.e. route choice *or* mode choice *or* departure time choice.

Against this background, the present chapter aims at linking methods of economic policy appraisal to the understanding of implementation problems of *non-monetary* and *monetary* policies when assuming income-dependent behavior in the choice model as well as multiple choice dimensions simultaneously. The agent-based model that is used for simulation is capable of simulating the complete daily plans of several million individuals (Meister et al., 2008). In contrast to traditional models, all attributes that are attached to the synthetic travelers are kept throughout the simulation process, enabling highly granulated analysis (Grether et al., 2010; Nagel et al., 2008). Being aware of all attributes offers the possibility to attach an individual utility function to every traveler which is used to maximize the individual return of travel choices during the simulation process. This approach therefore allows choice modeling and economic evaluation to be realized in a consistent framework. The individual utility functions proposed in this chapter assume continuously decreasing marginal utilities of money, and thus, Value of Travel Time Savings (VTTS) that continuously increase with income. Additionally, the model allows for multiple choice dimensions simultaneously, such as route choice *and* mode choice *and* departure time choice. The latter makes it possible to connect travelers' choices along the

time axis when simulating time-dependent policies (Grether et al., 2008). Simulation results can immediately be used to identify winners and losers, since the utility of the individual agents are kept and can be compared between scenarios agent-by-agent. They can also be aggregated in arbitrary ways, based on available demographic attributes including spatial information of high resolution. Welfare computations, if desired, can be done on top of that, without having to resort to indirect measures such as link travel times or inter-zonal impedances. The usual problems when aggregating or monetizing the individual utility still apply (Bates, 2006).

Please note that the contents of this chapter are edited versions of Kickhöfer et al. (2011) and Kickhöfer et al. (2010). The chapter forms the basis for answering Research Questions 1 and 2. The remainder of this chapter is organized as follows: After introducing the simulation framework in Sec. 3.2.1 and estimating the income-dependent utility functions in Sec. 3.2.2, three different Case Studies are conducted in Sec. 3.3 to Sec. 3.5: Case Study I verifies the correctness and plausibility of the estimated choice model, as well as the underlying implementation in a simple test scenario. The effect of a non-monetary policy on individual behavior and utility levels is analyzed for a global speed increase of the Public Transport (PT) mode. For Case Study II, this setup is transferred to a large-scale real-world scenario of the Zurich metropolitan area in Switzerland, and different aggregation and monetization procedures of individual utility changes from Sec. 2.3.3 are applied. In Case Study III, the approach is applied for a monetary policy in the Zurich scenario: it is shown how agents react to a morning peak toll for eight different distance toll levels. Again, agent-specific utility changes resulting from the pricing schemes are aggregated in two different ways in order to identify the welfare optimal toll level. This is followed by a comparison of the results for the two different aggregation procedures. Sec. 3.6 discusses the results of the Case Studies with regard to public acceptance issues and opportunities that emerge from the comparison of the different aggregation and monetization procedures. Finally, Sec. 3.7 summarizes the main findings and contributions of this chapter, and provides venues for further research.

3.2 Methodology

This section (i) gives a brief overview of the general simulation approach of the Multi-Agent Transport Simulation (MATSim), and (ii) describes the

estimation of the income-dependent utility functions, and how the obtained parameters are embedded in the MATSim framework.

3.2.1 Transport Simulation with MATSim

In the following, only general ideas about the transport simulation with MATSim are presented. For in-depth information about the simulation framework, please refer to Raney and Nagel (2006), or to Sec. 2.2.1, respectively.

In MATSim, each traveler of the real system is modeled as an individual agent. The modeling approach consists of an iterative loop which is composed of the following steps:

1. *Generating Plans*: All agents independently generate daily plans that encode among other things their desired activities during a typical working day as well as the transport mode for every intervening trip. One of these plans is marked as 'selected'.

2. *Simulating Mobility*: All selected plans are simultaneously executed in the simulation of the physical system.

3. *Evaluating Plans*: All executed plans are evaluated by a utility function which typically encodes the attributes travel time and monetary cost, as well as the perception of these attributes. The attributes typically vary within the available choice dimensions (route, mode, time, etc.).

4. *Learning*: Some agents obtain new plans for the next iteration by modifying copies of existing plans. This modification is done by several modules, one for every available choice dimension. The choice between plans is performed with respect to a Multinomial Logit (MNL) model where the total utility of all plans in the choice set enters.

The steps 'Generating Plans', 'Evaluating Plans', and 'Learning' represent the mental layer of the model which is needed for behavioral modeling. 'Simulating Mobility' exhibits the physical layer of the model which is needed to capture interaction between agents in a (capacity) constraint environment. The repetition of the iteration cycle coupled with the agent database enables the agents to improve their plans over many iterations. This is why it is also called learning mechanism. The iteration cycle continues until the system has reached a stable outcome.

3.2.2 Estimation of the Income-Contingent Utility Function

3.2.2.1 Approaches for the Integration of Income in Transport Policy Analysis

There is some agreement in the literature that income should be considered in transport policy analysis (see, e.g., Bates, 1987, 2006; Franklin, 2006; Herriges and Kling, 1999; Kockelman, 2001; Mackie et al., 2001; Small, 1983). The argument essentially is that monetary price changes affect people with different income differently. Conversely, if different income groups need to be compensated for losses or should be taxed for gains from non-monetary policies, the valuation of these offsetting payments is income-dependent.

Franklin (2006) studies the impact of a bridge toll on individual welfare by decomposing it into three different components and calculating the equivalent variation for all of them: first, the effect of paying the toll; second, the effect induced by travel time savings; and third, the benefits resulting from the use of the collected toll revenue. His findings indicate that a toll policy has regressive effects on the welfare distribution of society. The major impact stems from the toll payment itself. He then states that the benefits of travel time savings are also likely to be regressive. However, by using the toll revenue as a equal refund to all users of the bridge (car *and* public transport), the regressivity can fully be countered while still creating a net social benefit.

The second point is highly important for the present chapter. If travel time savings as a result of a non-monetary policy are also found to be regressive, then there is no toll revenue that can be used to offset regressivity. Furthermore, Franklin (2006) concludes that his analysis is rather limited because of a very simplified scenario: individuals are only allowed to switch mode as a reaction to the toll. Therefore, future work is needed where travel choices are modeled by incorporating time-of-day, destination, route, mode choice, and at the same time including income as a non-linear variable.

This chapter can be seen as a step into this direction. It demonstrates how these insights can be used constructively in an agent-based approach which is capable to model several choice dimensions simultaneously.

3.2.2.2 Estimation Data

Data for estimation of the travel related part of the utility function presented in this chapter is taken from surveys run by the Institute for Transport Planning and Systems at ETH Zurich (Vrtic et al., 2008). The surveys focused on the description of choices in terms of departure time,

mode and route choice. These were conducted as a combination of Revealed Preference (RP) and Stated Preference (SP) surveys: The objectives of the RP survey were on the one hand the recruitment of individuals, on the other hand capturing their current mobility behavior. Within the SP surveys, individuals were confronted with hypothetical alternatives (choice set). This choice set was generated based on the individual's reported trips by modifying the characteristics of at least one alternative. Individuals were then asked to make choices what results in one observation per decision; by estimating the coefficients of utility functions, the impact of the different variables on the decision making can be investigated and generalized.

In this chapter, the estimation of the late arrival penalty is based on the departure time and route choice part of the SP survey. The estimation of all other parameters uses data from the mode and route choice part of the SP survey. The sample size of the former survey is 531, of the latter 669 individuals. In each survey, individuals were confronted with seven choice situations.

3.2.2.3 Functional Form

The functional form of the travel related part of the (dis)utility functions used in this chapter is loosely based on Franklin (2006) and is similar to Kickhöfer (2009). In these studies, two transport modes are available: car and PT[1], characterized by the following initial utility functions[2]:

$$\begin{aligned} V_{car,i,j} &= & & & +\beta_c \cdot \ln(y_j - c_{i,car}) & +\beta_{tr,car} \cdot t_{i,car} \\ V_{pt,i,j} &= & \beta_0 & +\beta_c \cdot \ln(y_j) & +\beta_c \cdot \ln(y_j - c_{i,pt}) & +\beta_{tr,pt} \cdot t_{i,pt} \ , \end{aligned} \tag{3.1}$$

where y_j is the daily income of person j, c_i is monetary cost for the trip to activity i, and t_i the corresponding travel time. Monetary cost and travel time are mode-dependent, indicated by the indices. As defined in Sec. 2.3.2, $|\beta_c|$ is the marginal utility of money, β_{tr} is the mode-dependent marginal utility of travel time, and β_0 indicates a potential a-priori preference for one of the transport modes. Additionally, $\beta_c \cdot \ln(y_j)$ could pick up an income-dependent a-priori preference for one of the transport modes. Daily

[1] In this chapter, every agent is assumed to have a car available, i.e. there are no PT captives.

[2] In this chapter, these initial utility functions build the basis for replacing the travel related part of utility from Eq. 2.3.

income y_j is obtained by the following calculation:

$$y_j = \frac{y_{year,HH}}{n_{HH} \cdot 240} \ ,$$

where $y_{year,HH}$ depicts the income of the household per year, n_{HH} the number of persons in the household and 240 the number of working days per year.

Unfortunately, it is not possible to use the functional form in Eq. 3.1 directly for parameter estimation, since the survey data contains relatively long trips, meaning that $y_j - c_i$ can become negative, in which case $\ln(y_j - c_i)$ is not defined.[3] To circumvent this problem, Taylor's theorem is used to approximate the logarithm by applying

$$\ln(y_j - c_i) \approx \ln(y_j) - c_i \cdot [ln(y_j)]' = ln(y_j) - \frac{c_i}{y_j} \ , \tag{3.2}$$

which results into a $1/y_i$ dependency of the cost term and, thus, seems plausible. Applying Eq. 3.2 to Eq. 3.1 and estimating the parameters[4]

$$\hat{\beta}_c = 4.58 \ , \qquad \hat{\beta}_{tr,car} = -2.83/h \ , \qquad \text{and} \qquad \hat{\beta}_{tr,pt} = -1.86/h \ ,$$

leads to the following functional form:

$$\begin{aligned} V_{car,i,j} &= 4.58 \ \ln(y_j/CHF) - \frac{4.58}{y_j} c_{i,car} - \frac{2.83}{h} t_{i,car} \\ V_{pt,i,j} &= 4.58 \ \ln(y_j/CHF) - \frac{4.58}{y_j} c_{i,pt} - \frac{1.86}{h} t_{i,pt} \end{aligned} \tag{3.3}$$

It might be a bit surprising that the marginal utility of travel time comes out higher for car than for PT. It is, however, consistent with the higher costs of $c_{pt} = 0.28 \ CHF/km$[5] assumed for PT than for car ($c_{car} = 0.12 \ CHF/km$), which were used in the survey (Vrtic et al., 2008) and will be used in

[3] One may argue that in such cases the model should reject the journey completely, at least if it is a regular journey (M. Wegener, personal communication).

[4] Estimated parameters are in this chapter flagged by a hat. For estimation, the tool BIOGEME is used; it provides a maximum-likelihood estimation for utility parameters (Bierlaire, 2003). For more information, please see `http://biogeme.epfl.ch/`. Both, the income-dependent Alternative Specific Constant (ASC) $\beta_c \cdot \ln(y_j)$ and the general ASC β_0 from Eq. 3.1 were estimated not significantly different from zero and are therefore not further considered. This essentially means that neither an income-dependent nor a general a-priori preference is found for one of the transport modes. All other parameters are found to be significant on a a level of 5%.

[5] 1 CHF = 1 Swiss Franc $\approx$ 0.85 EUR, exchange rate on 09.07.2013.

the simulations. Clearly and somewhat unusual, for Switzerland, PT is the higher value mode compared to car. Because of this specification, VTTS are income- *and* mode-dependent. The VTTS for the median income of the sample ($y_{median} = 155$ CHF per person and day) turn out to be approximately 96 CHF/h for car and 63 CHF/h for PT, respectively. These values are two to three times higher as those in Vrtic et al. (2008). Thus, the inclusion of income in the utility function seems to have unintended impacts on the VTTS. This effect should be addressed in future research. However, note that, e.g., the VTTS for PT varies from 7 to 330 CHF/h along the income range, which naturally includes the values from the linear model in Vrtic et al. (2008).

Another open question at this point is how much of the estimated marginal utility of travel times $\hat{\beta}_{tr}$ are opportunity costs of time[6], and how much is an additional disutility caused by traveling β_{tr} in the corresponding mode. Unfortunately, these values cannot be obtained from the survey as it was taken. In the follwing, it is therefore assumed that traveling in PT neither adds nor subtracts from the opportunity cost of time. This implies $\beta_{perf} = 1.86/h$ in Eq. 2.2, and modifies the travel related part of the utility functions to

$$\begin{aligned} V_{car,i,j} &= 4.58\ \ln(y_j/CHF) - \frac{4.58}{y_j}\, c_{i,car} - \frac{0.97}{h}\, t_{i,car} \\ V_{pt,i,j} &= 4.58\ \ln(y_j/CHF) - \frac{4.58}{y_j}\, c_{i,pt}\ . \end{aligned} \tag{3.4}$$

The marginal utility for being late $\hat{\beta}_{late}$ is estimated similar to Kickhöfer (2009): in a time and route choice survey from ETH Zurich (Vrtic et al., 2008) people stated their willingness-to-pay in order to reduce the probability of being late. Based on this data, $\hat{\beta}_{late}$ is estimated and then re-scaled with respect to the cost related behavioral parameter $\hat{\beta}_c$ and the average income of the sample $\overline{y} = 172$ CHF per day in Eq. 3.3. This results in $\beta_{late} = 1.52/h$.[7]

[6] For an introduction to 'opportunity costs of time' in the MATSim framework, see Sec. 2.2.1.3. This interpretation is consistent with the literature where there is an inherent opportunity cost of time and additional utilities or disutilities depending on how the time is spent (Börjesson and Eliasson, 2014; DeSerpa, 1971; Jara-Díaz, 2003).

[7] The parameter for late arrival will only be used in the following section for Case Study I (Sec. 3.3), but not for the real-world scenarios of Zurich metropolitan area in Sec. 3.4 and Sec. 3.5.

Applying Eq. 3.4, Eq. 2.4, and Eq. 2.2 to Eq. 2.1, as well as inserting the estimated parameters, results in the two final utility functions used in this chapter, which are selected depending on the mode of the ith trip:

$$\begin{aligned} V_{car,i,j} &= \frac{1.86}{h}\, t_{*,i} \cdot \ln(\frac{t_{perf,i}}{t_{0,i}}) - \frac{1.52}{h}\, t_{late,i} - \frac{4.58}{y_j}\, c_{i,car} \quad - \frac{0.97}{h}\, t_{i,car} \\ V_{pt,i,j} &= \frac{1.86}{h}\, t_{*,i} \cdot \ln(\frac{t_{perf,i}}{t_{0,i}}) - \frac{1.52}{h}\, t_{late,i} - \frac{4.58}{y_j}\, c_{i,pt} \end{aligned} \tag{3.5}$$

The income-related offset $+4.58\ \ln(y_j/CHF)$ in Eq. 3.4 can be interpreted as the utility earned from daily income. It is therefore calculated once for each individual, added to the overall utility of daily plans, and is removed from the activity related functions in Eq. 3.5.

Because of the argument regarding the opportunity cost of foregone activity time when arriving early (see Sec. 2.2.1.3), the *effective* marginal disutility of early arrival is $\beta_{early_{eff}} = -\beta_{perf} \cdot t_{*,i}/t_{perf,i} \approx -\beta_{perf} = -1.86/h$ which is equal to the *effective* marginal disutility of traveling with PT $\beta_{tr,pt_{eff}}$. The *effective* marginal disutility of traveling by car is, by the same argument, $\beta_{tr,car_{eff}} = -\beta_{perf} \cdot t_{*,i}/t_{perf,i} + \beta_{tr,car} \approx -\beta_{perf} + \beta_{tr,car} \approx -2.83/h$.

For Case Study I, the *effective* values of car travel time would correspond to the values $(\beta_{early_{eff}}, \beta_{tr,car_{eff}}, \beta_{late_{eff}}) = (-1.86,\ -2.83,\ -1.52)$ of the Vickrey bottleneck scenario (Arnott et al., 1990; Vickrey, 1969).

3.2.2.4 Income Generation

Income is generated equally to Grether et al. (2009b) who use real-world data for an approximation of the Lorenz curve[8]. Then the Lorenz-income curve, the first derivative of the Lorenz curve, is calculated (Kämpke, 2010).[9] To generate personal incomes for the agents, a random number between 0 and 1 is drawn from a uniform distribution. For this number, the corresponding value on the income curve is calculated and multiplied by the—possibly regionally differentiated—median income. Doing this for all members of the synthetic population, an income distribution is derived, similar to the distribution in reality. Adding income at an individual level results in a personalized utility function for each agent. For Case Study I in the following section, income is the only varying attribute between agents.

[8] The Lorenz curve denotes the relative cumulative income of the $100 \cdot x\%$ lowest incomes at any point x. For further information, see, e.g. Kämpke (2010).

[9] The Lorenz curve is $L(x) \propto \int_0^x y(\xi)\, d\xi$. Therefore, $L'(x) \propto y(x)$. The correct scaling is given by the fact that $y(0.5)$ is the median income.

The real-world scenario in the subsequent section, however, includes varying trip distances and daily plans so that demographic attributes of each agent are strongly personalized.

3.3 Case Study I: PT Speed Increase—Test Scenario

The goal of this section is to verify the correctness and plausibility of the estimated choice model and the underlying implementation. A simple setup is used in order to test the plausibility of traveler choice reactions resulting from a policy change.

3.3.1 Scenario Setup

Network The test network (see Fig. 3.1) consists of a cycle of one-way links with (unrealistically) high capacities so as to minimize their influence on traffic patterns, essentially making it possible for agents to drive with free speed. One link between home and work location has reduced capacity of 1000 vehicles per hour, building a bottleneck. The distance from the home to the work location of the agents is 17.5 km, the way back is 32.5 km long. Speed limit is at 50 km/h so the free speed travel time from home to work by car is 21 min while 39 min are needed for the way back home. Thus, the total free speed travel time by car is 60 min. As the agents are forced to remain on that route, the scenario is similar to the Vickrey bottleneck scenario (Arnott et al., 1990; Vickrey, 1969).

Population The synthetic population consists of 2000 agents. All agents start at their home activity, which they initially leave at 6:00 a.m. They initially drive to work by car, where they initially stay for 8 h, and then drive home again.

In addition, each agent initially possesses an non-active plan that uses the PT mode for both trips. These trips take twice as long as by car at free speed, i.e. 42 min from home to work, and 78 min for the way back. Thus, the total PT travel time is 120 min. In contrast to the car travel times, these PT travel times are not affected by congestion. Since PT is assumed to run continuously and without capacity restrictions, a home departure at time t will always result in a work arrival at $t + 42$ min. Estimation of income for the synthetic population, as described in Sec. 3.2.2.4, is based

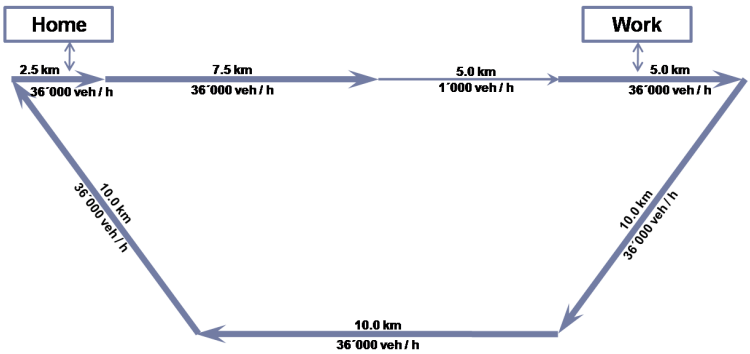


Figure 3.1: The layout of the test network with link attributes. Traffic runs clockwise starting at the home location. Between home and work location, there is a bottleneck with restricted capacity of 1000 veh/h.

on values for the Kanton[10] Zurich in 2006. The median income for that year is 46'300 *CHF* per household.

Activities Work opens at 7:00 a.m. and closes at 6:00 p.m. This means that no utility can be accumulated from an arrival earlier than 7:00 a.m. The latest start time of the work activity is set to 7:00 a.m. That is, any arrival later than 7:00 a.m. is immediately punished with $\beta_{late} = -1.52/h$. The home activity is *wrapped around*,i.e. a departure at 6:00 a.m. and a return at 5:00 p.m. results in a home activity duration of 13 h. *Typical* durations of $t_{*,work} = 8\ h$ and $t_{*,home} = 12\ h$ mean that work and home times have a tendency to arrange themselves with a ratio of 8:12 (i.e. 2:3).

3.3.2 Policy Design and Simulation Procedure

The policy that will be analyzed in this Case Study is a global speed increase of the PT mode. That is, traveling by PT now takes only 1.8 (instead of 2.0) times as long as traveling by car on an empty network (see Sec. 2.2.1.2). This corresponds to a PT speed increase of 10%. User costs[11] for car are set to 0.12 CHF/km, and to 0.28 CHF/km for PT.

[10] A Swiss *Kanton* is similar to a federal state.
[11] Please note that the term 'user costs' is referred to as out-of-pocket costs for the users.

For choosing between travel alternatives, the re-planning modules MCMa) and TCM from Sec. 2.2.1.4 are used. For the base case, the simulation is set up as follows:

- For 2000 iterations, 10% of the agents perform time adaptation with a mutation range of 7.5 *min*. The other 90% of the agents switch between their existing plans according to Eq. 2.5, which means in this setup that they potentially also switch the transport mode.

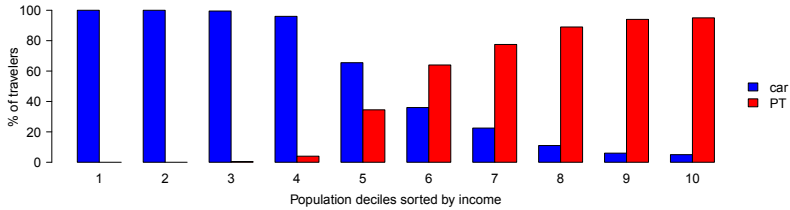
- Between iteration 2001 and 4000, time adaptation is switched off; in consequence, agents only switch between existing options according to Eq. 2.5. That is, their choice set now remains fixed to what they have found in the first 2000 iterations, and they choose within this set according to a MNL model.

The output of iteration 4000 is then used as input for the policy case which is run for another 2000 iterations. Again, for the first 1000 iterations, the time adaptation module is again switched on, with the same 10% re-planning rate. The final 1000 iterations are once more performed with a fixed choice set. For further analysis, iteration 4000 of the base case is then compared to iteration 6000 of the policy case.

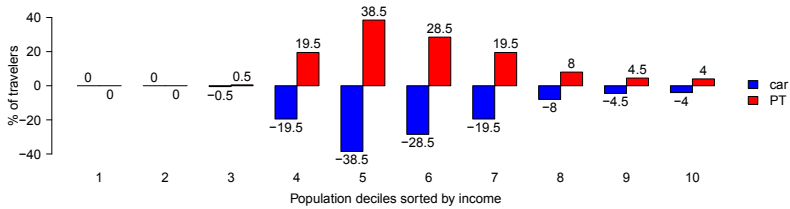
3.3.3 Results

Since car is the low value and PT the high value mode, low income people predominantly use the car while high income people predominantly use PT (Fig. 3.2(a)). When the PT speed is increased, the overall modal split predictably shifts from car to PT, from 54% : 46% to 42% : 58% (car:PT). Also predictably but importantly, this happens through a shift of the income level that divides the two regimes—this level, naturally, moves to lower incomes (Fig. 3.2(b)).

Fig. 3.3 shows, agent-by-agent, the utility differences between the base case and the policy case as a scatter plot over deciles of the population. Every decile, summed up over all three plots, contains the same number of agents, sorted by their income. For example, the first decile includes the 10% of agents with the lowest incomes. Fig. 3.3(a) shows synthetic travelers that choose the same transport mode before and after the policy change, blue crosses for the car mode, red circles for the PT mode. One notices a homogeneous utility increase of roughly 0.35 *utils* (or 11 *min*) for the PT users, and a smaller increase of about 0.25 *utils* (or 8 *min*) for



(a) Base case

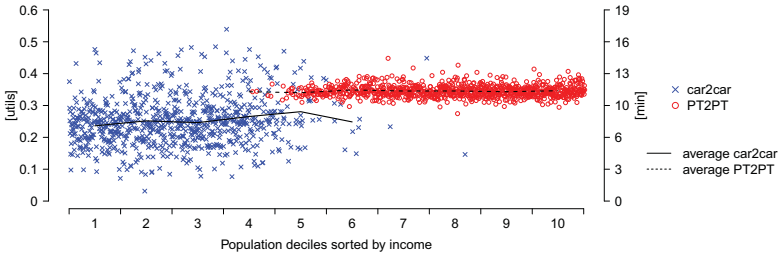


(b) PT speed increase

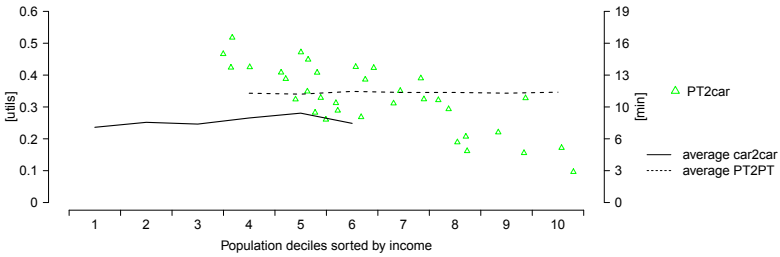
Figure 3.2: Modal split over deciles of the population, sorted by income. Absolute values for the base case, changes in percentage points for the PT speed increase. Blue bars depict car drivers, red bars PT users.

the car users.[12] This is a plausible consequence of the fact that PT users benefit directly from the policy, while car users benefit from congestion relief because of the reduced car mode share. The car users face, because of stochastic congestion effects, rather strong fluctuations of their utilities from iteration to iteration. This effect can also be observed when comparing the base case to the policy case. For PT users, these fluctuations are much less pronounced because of their—by assumption—completely reliable transport mode. Figs. 3.3(b) and 3.3(c) show synthetic travelers that change their transport mode, Fig. 3.3(b) from PT to car and Fig. 3.3(c) from car to PT, respectively. With the PT improvement, a switch from PT to car

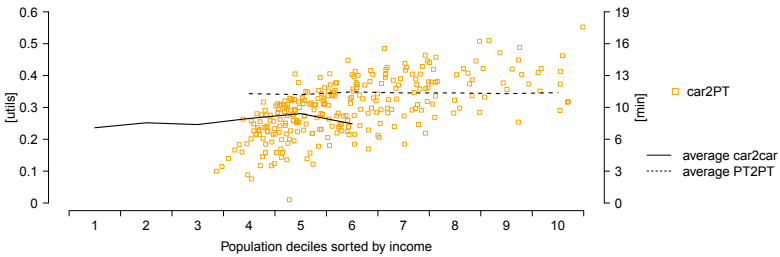
[12] Utility differences in *utils* are calculated by subtracting the utility of the executed plan before the policy from the utility of the executed plan after the policy (see Sec. 2.3.2). In the strict sense, these utility differences have no meaning, as discussed in Sec. 2.1.2. Therefore, time equivalents in *min* are used for interpersonal comparison. They are calculated following the approximation in Sec. 2.3.3.3 by multiplying the individual utility changes with the inverse marginal utility of time $\left(\frac{\partial V}{\partial t}\right)^{-1} \approx \frac{1}{\beta_{perf}}$.



(a) Synthetic travelers who keep their mode



(b) Synthetic travelers who switch from PT to car



(c) Synthetic travelers who switch from car to PT

Figure 3.3: Changes in utility [*utils*] and approximate time equivalents [*min*] over deciles of the population, sorted by income. Every synthetic traveler is plotted according to her relative position on the income scale. The lines in Figs. 3.3(b) and 3.3(c) denote the average changes for users keeping their mode from Fig. 3.3(a).

(Fig. 3.3(b)) is not what should be expected. These synthetic travelers are therefore *logit switchers*, in the following sense:

- Those who gain more than the average by the switch, towards the lower income scales, are travelers that could already have achieved a higher utility level in the base case by using car.
- Those that gain less than the average by the switch, towards the higher income scales, are travelers that would have gained even more by staying with PT.

However, in both cases the utility computation is done according to the systematic component of utility as described in Sec. 2.2.1.3. The switches are therefore caused by changes in the random component of utility ϵ. Fig. 3.3(c) also contains *logit switchers*, this time from car to PT. But in addition, it also contains *systematic switchers* who change the mode because of a utility gain in the systematic component. The density of switchers is largest towards middle income groups, since there, the systematic switchers are located. One could, in principle, also attach the random components as random but fixed to every alternative of every traveler.[13] Karlstrom and Morey (2004) and therefore Franklin (2006) also assume such interpretation in their welfare computations.

In the following, the results are interpreted with respect to the *rule-of-half* (Daly et al., 2008; Jara-Díaz, 2007). According to that rule, the pre-existing users of an improved facility obtain the full utility gains, whereas the users switching towards the improved facility in average obtain half of those gains. In the present case, the situation gets more complicated because of substitution effects: Also users not using the improved facility gain because of congestion relief. Differentiated by user groups, one obtains:

- Average gain when staying with PT: 0.345 *utils* ($\approx$ 11.129 *min*)
- Average gain when switching from car to PT: 0.297 *utils* ($\approx$ 9.580 *min*)
- Average gain when staying with car: 0.250 *utils* ($\approx$ 8.064 *min*)

As one can see, the switchers from car to PT indeed gain, in the population average, the mean value between the (direct) PT gains and the (indirect) car gains. Nevertheless, the situation is confounded by the fact that there

[13] For an example in location choice using the MATSim framework, please refer to Horni et al. (2012).

are also significant gains for the car users, which could not be computed by considering the PT facility alone.

Overall, the results demonstrate that the presented approach with income-dependent user preferences has the expected impact on behavioral reactions of users. The PT quality-of-service improvement leads to a higher mode share of PT, mainly caused by medium income users that systematically switch mode. In terms of time equivalents, users staying with car gain less than users staying with PT. As expected, the systematic mode switchers on average gain the mean value between these two. The distribution of the time gains of this last group increases with income, but less than proportional. Finally, these observations show that the approach allows for a detailed analysis how individual utility levels are affected by a policy. Thus, the plausibility test can be regarded as successful. While this Case Study only provided results in terms of (individual) time equivalents, the following Case Studies will additionally deal with the impact of the different aggregation and monetization rules for utility differences that were presented in Sec. 2.3.3.

3.4 Case Study II: PT Speed Increase—Zurich, Switzerland

The income-dependent utility function is now applied to a large-scale, real-world scenario. The area of Zurich, Switzerland, is used which counts about 1 million inhabitants. The following paragraphs give a simplified description of the scenario and focus on differences to similar simulations done by Chen et al. (2008).

3.4.1 Scenario Setup

Network The network is a Swiss regional planning network that includes the major European transit corridors. It consists of 24'180 nodes and 60'492 links.

Population The simulated demand consists of all travelers within Switzerland that are inside an imaginary 30 km boundary around Zurich at least once during their day (Chen et al., 2008; Vrtic et al., 2007). All agents initially have two daily plans that encode their reported activities during a typical working day. This information is taken from micro-census information (SFSO, 2000, 2006). The first plan only uses car as transport mode, while the second plan only uses PT.

Income for the large-scale scenario is generated as described in Sec. 3.2.2.4. Region specific data is used for the Kanton Zurich since here, income medians are available for each municipality.[14] For every person living in the Kanton Zurich, the municipality of the person's home location is determined. Then the median income specific for this municipality is used for income calculation in conjunction with a Lorenz curve for the Kanton Zurich.[15] Incomes for persons living outside the borders of Kanton Zurich are computed with the help of the median income and the Lorenz curve of the Swiss Confederation.[16] The median income used for the Swiss Confederation in 2006 is 43'665 *CHF* per household and year.

Activities Activities are classified as *home*, *work*, *education*, *shopping*, and *leisure*. The time window during which activities can be performed is limited to certain hours of the day: *work* and *education* can be performed from 7:00 a.m. to 6:00 p.m., *shopping* from 8:00 a.m. to 8:00 p.m. This means that for these activities no utility can be accumulated outside of the opening times. In contrast, *home* and *leisure* have no time restrictions. Unlike Case Study I, there is no punishment for being late. This is not possible because agents can have more than one work activity, e.g. one in the morning and one in the afternoon. In such a case it is complicated to specify when an agent starts an activity late or not.

3.4.2 Policy Design and Simulation Procedure

The policy for this Case Study is identical to the one in Case Study I: a global speed increase of the PT mode by 10% (see Sec. 3.3.2). Also user costs are identical, namely 0.12 CHF/km for car and 0.28 CHF/km for PT. To speed up computations, a random 10% sample is taken from the synthetic population for simulation, consisting of 181'725 agents. In order to maintain consistency with Case Study I, the total amount of iterations is reduced, but the proportion of the different simulation steps is kept constant. Now, the re-planning modules RCM, MCMa), and TCM from Sec. 2.2.1.4 are used. They allow for route choice, mode choice, and departure time choice, respectively:

[14] http://www.web.statistik.zh.ch/themenportal/themen/daten_detail.php?id=759, last access: 20.05.2011

[15] http://www.web.statistik.zh.ch/themenportal/themen/aktuell_detail.php?id=2752&tb=4&mt=0, last access: 20.05.2011

[16] http://www.bfs.admin.ch/bfs/portal/de/index/themen/20/02/blank/dos/01/02.html, last access: 20.05.2011

- For 1000 iterations, 10% of the agents perform time adaptation and 10% adapt routes. The other 80% of the agents switch between their existing plans, which implicitly includes mode choice as explained in Sec. 2.2.1.2.

- During the second 1000 iterations, time and route adaptation are switched off; in consequence, agents only switch between existing options according to Eq. 2.5.

After introducing the PT speed improvement, the policy case is continued for another 1000 iterations, starting from the final iteration of the base case. Again, during the first 500 iterations 10% of the agents perform time adaptation while another 10% of agents adapt routes. Agents neither adapting time nor route switch between existing plans and such eventually switch between transport modes. For the final 500 iterations only a fixed choice set is available. For evaluating the impact of the PT speed increase, iteration 2000 of the base case is compared to iteration 3000 of the policy case.

3.4.3 Validation of the Base Case

Simulated traffic volumes are compared with the hourly traffic volumes from 159 real-world counting stations. In Fig. 3.4, circles indicate the mean relative error of the reference Zurich scenario (Chen et al., 2008) between hourly flows in reality and hourly flows from the simulation. That model was based on $\beta_{perf} = 6/h$, $\beta_{tr,car} = -6/h$, $\beta_{tr,pt} = -3/h$, and no dependence on travel distance or income was assumed. The triangles depict the same for the estimated income-dependent utility functions. One notices a slight improvement of the mean relative error, especially during day time in comparison with Chen et al. (2008). This underlines the advantage of using estimated behavioral parameters for more realistic results. Nevertheless, it is a bit surprising that, at least at the aggregated level, there is so little difference between the simulations. Presumably, this is due to the fact that the activity patterns, preferred activity durations, opening times, and transportation network structure are dominating the results. In particular, given the fact that the traffic counts are reproduced much better between 8:00 a.m. and 7:00 p.m. than the remainder of the day, one may speculate that the need to squeeze all activities into the available opening times is, in fact, the dominating force.

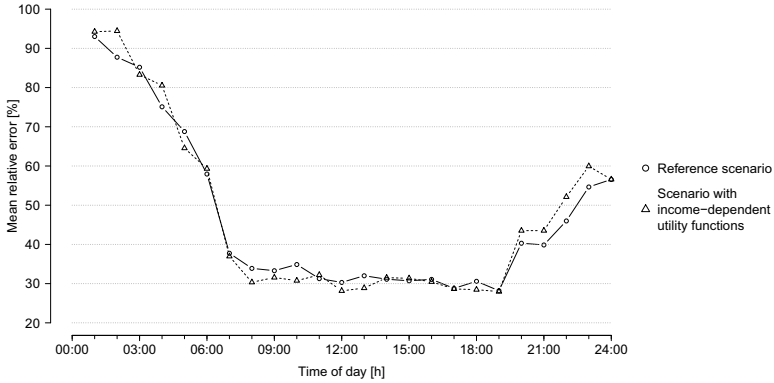


Figure 3.4: Realism of the two simulations. Hourly comparison of simulation traffic flows with data from 159 traffic counting stations in the Zurich area. Circles show the mean relative error for the reference scenario, triangles for the scenario using income-dependent utility functions.

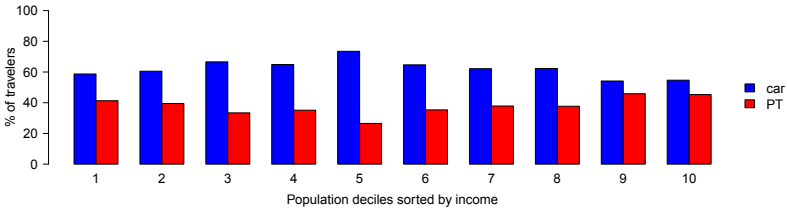
Together with the analysis of other traffic condition indicators, such as peak hours, modal split or the average trip duration or length, it can be stated that the base case seems to be a good starting point for investigating the PT speed increase.

3.4.4 Results

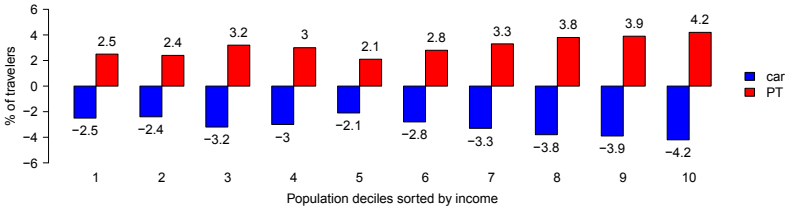
The base case of the Zurich scenario exhibits a modal split of 60.9% : 39.1% (car:PT). Fig. 3.5(a) depicts the modal split over income deciles of the population. In contrast to the base case of Case Study I (see Fig. 3.2(a)), the distribution here is more homogeneous: Both modes are used across all deciles. Fig. 3.5(b) presents changes to the modal split over income deciles of the population compared to the base case. One can observe a tendency that with increasing income, more individuals switch from car to PT.

Fig. 3.6 shows, that in contrast to Case Study I, average gains in terms utility or approximate time equivalents[17] barely increase for higher incomes

[17] Identically to Case Study I, every agent's utility difference in *utils* is calculated by subtracting the utility of the executed plan before the policy from the utility of the executed plan after the policy (see Sec. 2.3.2). Averages are calculated for every income decile. Since, in the strict sense, the aggregation of utility differences of different individuals is methodologically problematic (see Sec. 2.1.2), approximate



(a) Base case



(b) PT speed increase

Figure 3.5: Modal split over deciles of the population, sorted by income. Absolute values for the base case, changes in percentage points for the PT speed increase. Blue bars depict car drivers, red bars PT users.

deciles. Each data point is located in the middle of an income decile and represents the corresponding average change over the whole population with a black triangle. For representation purposes the data points are connected with lines. These overall gains of roughly 0.15 *utils* or 4.84 *min* are mainly composed of the average changes of two different user groups: As expected, synthetic persons using PT both before and after the PT improvement (represented by red circles) obtain most of the benefits, i.e. 0.21 to 0.24 *utils* or approximately 6.77 to 7.74 *min*. Synthetic persons using car both before and after the policy (represented by blue crosses) also gain, but considerably less than the PT users, i.e. 0.07 to 0.11 *utils* or 2.26 to 3.55 *min*. Results for the mode switchers are not shown because the stochastic fluctuations overwhelm the signal. Even though the slope of the curves is slightly positive, average gains are rather distributed quite equally across income deciles. However, as Fig. 3.7 shows, this picture completely changes when using income equivalents (see Sec. 2.3.3.1) for the aggregation

time equivalents in *min* are used for interpersonal comparison. The calculation is described in Sec. 2.3.3.3.

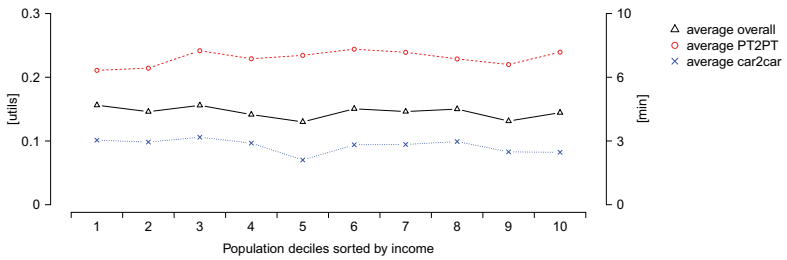


Figure 3.6: Average changes in utility [$utils$] and approximate time equivalents [min] over deciles of the population, sorted by income. Black triangles depict the overall change in the corresponding income decile. Blue crosses indicate the change for car users who keep their mode, red circles for PT users who keep their mode.

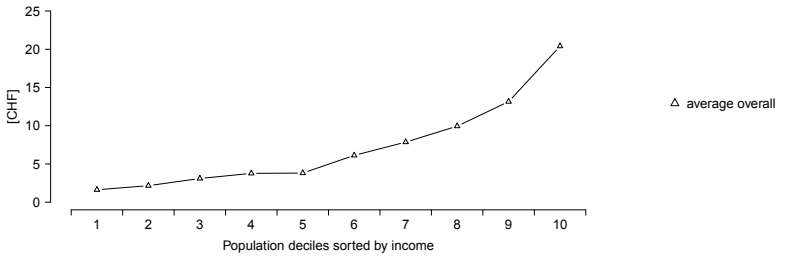


Figure 3.7: Average changes in income equivalents [CHF] over deciles of the population, sorted by income. The data points correspond in every income decile with the average willingness-to-pay for the PT speed increase.

of utility differences. The figure presents the average willingness-to-pay for the PT speed increase of the individuals in the corresponding income decile. As one can see, all income deciles still gain, but these gains are rather unequally distributed, ranging from 1.62 *CHF* for the lowest income decile to 20.40 *CHF* for the highest income decile. Clearly, this is due to the fact that the marginal utility of money was assumed to decrease with income, and therefore the conversion factor from utility into money terms given by $-\left(\frac{\partial V}{\partial c}\right)^{-1} = -\frac{1}{\beta_c} = \frac{y_j}{4.58}$ increases with income (see Eq. 2.13 and Eq. 3.5).

Overall, the Case Studies I and II have shown for a non-monetary policy that the approach is able to pick up the heterogeneity of users in terms of behavioral modeling. Additionally, the results from Case Study II show for the subsequent economic evaluation that the choice of monetizing and aggregating utility differences leads to vastly different results: while a conversion into time equivalents shows benefits to be rather equally distributed among income deciles, a conversion into income equivalents predicts higher benefits on the upper end of the income range. Since, for the PT speed increase, most individuals gained in terms of utility, the next Case Study will focus on a pricing policy where there are winners and losers, and investigates how the different monetization and aggregation procedures will in that case influence the results.

3.5 Case Study III: Morning Peak Toll—Zurich, Switzerland

After having identified implications of an income-dependent utility function on the economic evaluation of a non-monetary policy in the previous section, this case study now investigates the impacts of a pricing policy. Therefore, a distance-based morning peak toll is introduced for the municipality of Zurich, Switzerland. Toll levels are varied in parametric simulations in order to identify the welfare optimal price level. The goals are (i) to understand the implications of different aggregation / monetization methods of individual utility changes on this optimal toll level, and (ii) to derive possible consequences with respect to public acceptance issues that might result from the choice between these aggregation methods.

3.5.1 Scenario Setup

The initial scenario setup for this case study is identical to the one presented in Sec. 3.4.1. The monetary policy that will be investigated in this Case

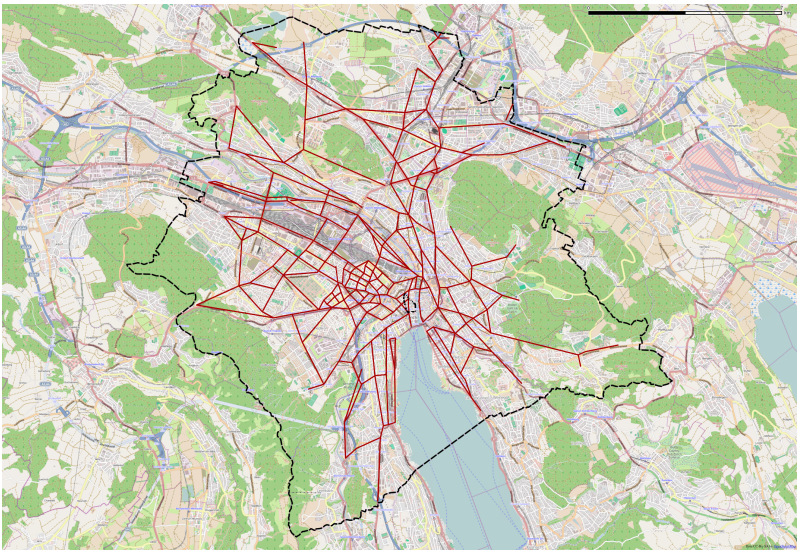


Figure 3.8: Policy design of the morning peak toll. Road segments (in red) where the toll applies. Source: author's image using map data from `www.openstreetmap.org` (© OpenStreetMap contributors).

Study, is described next.

3.5.2 Policy Design and Simulation Procedure

Policy Design The toll area design is taken from similar studies by Nagel et al. (2008). It covers, as can be seen in Fig. 3.8, all roads within the area of Zurich municipality, except the motorways that lead into and partially around the city. Since the latter are owned by the Swiss Confederation and not by the city of Zurich, they could not easily be taken into account when the local government decides about the implementation of a city toll. In addition, the proposed setup is expected to lead to more concentrated car traffic flow on the motorways while pulling flows from residential areas. Therefore, in 2007, some form of this road pricing scheme had been discussed to be implemented (Bundesrat (Government) of Switzerland, 2007). Based on this toll road network, eight different toll levels are now simulated in addition to the base case:

- Base case: user costs for car are set to 0.12 CHF/km, user costs for PT to 0.28 CHF/km
- Policy case 1: 0.35 CHF/km additional costs for cars on tolled links
- Policy case 2: 0.70 CHF/km additional costs for cars on tolled links
- Policy case 3: 1.40 CHF/km additional costs for cars on tolled links
- Policy case 4: 2.80 CHF/km additional costs for cars on tolled links
- Policy case 5: 5.60 CHF/km additional costs for cars on tolled links
- Policy case 6: 11.20 CHF/km additional costs for cars on tolled links
- Policy case 7: 22.40 CHF/km additional costs for cars on tolled links
- Policy case 8: 44.80 CHF/km additional costs for cars on tolled links

The toll is implemented for the morning peak from 6:30 a.m. to 9:00 a.m. This approach helps at finding a toll level near to the optimal toll for this particular system at this time of day only by observing welfare changes over different toll levels. From an economic point of view, the optimal toll is the one where the sum of monetized utility differences and toll payments is maximized.

Simulation Procedure To speed up computations, a random 10% sample is taken from the synthetic population for simulation, consisting of 181'725 agents. For choosing between travel alternatives, the re-planning modules RCM, MCMa), and TCM from Sec. 2.2.1.4 are used. They allow for route choice, mode choice, and departure time choice, respectively. The car traffic flow simulation and the simulation of other modes follow the description in Sec. 2.2.1.2. That is, travel times for PT are approximated by multiplying free flow car travel times by a factor of 2.0. For the base case, the simulation is set up as follows:

- For 1000 iterations, 10% of the agents perform time adaptation and 10% adapt routes. The other 80% of the agents switch between their existing plans, which implicitly includes mode choice as explained in Sec. 2.2.1.2.

- During the second 1000 iterations, time and route adaptation are switched off; in consequence, agents only switch between existing options according to Eq. 2.5.

This means, that during the first 1000 iterations, the *choice set* is being generated; during the second 1000 iterations, where time and route adaptation are switched off, agents actually carry out their choice by only switching between existing options. In the following, the output after 2000 iterations is referred to as the *base case*.

After introducing the distance tolls, the eight different policy cases are continued for another 200 iterations, starting from the final iteration of the base case. Again, during the first 100 iterations 10% of the agents perform time adaptation while another 10% of agents adapt routes. Agents, who neither adapt time nor route, switch between existing plans according to Eq. 2.5 which also includes the switch between transport modes. As for the base case, during the final 100 iterations only a fixed choice set is available. For evaluating the impact of the distance toll, iteration 2000 of the base case is compared to iteration 2200 of the policy case.

3.5.3 Results

In this section, the simulation results are presented. Overall, nine scenarios have been analyzed, the base case and eight policy cases with increasing toll levels (see Sec. 3.5.2). In the following, direct observations of traffic conditions as well as the actual behavior of the agents are discussed. Subsequently, in order to compare the different policies, the overall welfare effect is computed for two different interpretations of how to value the individual utility changes (see Sec. 2.3.3). Finally, the results are interpreted in the context of public acceptance of urban road pricing schemes. Please note that for reasons of clarity, not all nine simulation runs are always discussed; the analysis always contains the lowest and the highest toll level in order to get an estimate about the range of possible impacts.

3.5.3.1 Traffic Conditions

As discussed in Sec. 2.2.1, agents have several possibilities to react to changes of the system, such as the introduction of a road pricing scheme. In this study, they can (i) change their transport mode, (ii) change their car routes or (iii) adapt the departure time. Location choice is not considered, and agents can not drop activities from their schedule.

Picking up the first point, Fig. 3.9 shows a shift in the modal split as a consequence of the toll. The percentage of car trips between activities monotonously drops from 61% in the base case to 57% for the highest toll. This effect is likely to be even more important when only looking at people who have an activity within the toll area. Route and departure time adaptation could be analyzed independently, but at this point, a locally more differentiated indicator about the overall impact of the different toll levels on the actual traffic conditions is used: the average speed in central Zurich. Fig. 3.10 shows the average speed on all links in within a 2 km radius around the center of the city over time of day for several toll levels and for time bins of 5 min. For the base case (blue line), it can be seen that the average car speed in this area drops from 42 km/h at 6:00 a.m. to about 34 km/h at 6:30 a.m. It then raises again, up to round about 37 km/h, stays more or less constant until the afternoon peak starts at 4:00 p.m. For the lowest toll case, one can notice a slight improvement of the average speed in the morning hours from 7:00 a.m. on, represented by the red line in Fig. 3.10. With the toll level of 2.80 CHF/km (light blue line), this effect is even more important. Toll levels of 11.20 CHF/km and 44.80 CHF/km, represented by orange and green lines, respectively, additionally influence the average speed in the afternoon peak in a positive way. Furthermore these high toll levels indicate that there might exist a prohibitive toll level where no agent will take the car for traveling into or out of the city center. This fact is underlined by the decreasing number of people who pay toll during the day when raising the toll level: while for the lowest toll level, there are 110'160 agents paying toll, this number drops to only 18'770 agents for the highest toll case.[18] This corresponds to 6% or 1% of the whole population, respectively. The total payments for these two policy cases amount to 151'376 CHF and 1'386'129 CHF.[19]

3.5.3.2 Economic Evaluation

Similar to the analysis in Case Study II, Fig. 3.11 shows the average gains in terms of utility or approximate time equivalents[20] over deciles of the

[18] Values scaled to full population.

[19] Values scaled to full population.

[20] Again, every agent's utility difference in $utils$ is calculated by subtracting the utility of the executed plan before the policy from the utility of the executed plan after the policy (see Sec. 2.3.2). Averages are calculated for every income decile. Since, in the strict sense, the aggregation of utility differences of different individuals is methodologically problematic (see Sec. 2.1.2), approximate time equivalents in min are used for interpersonal comparison. The calculation is described in Sec. 2.3.3.3.

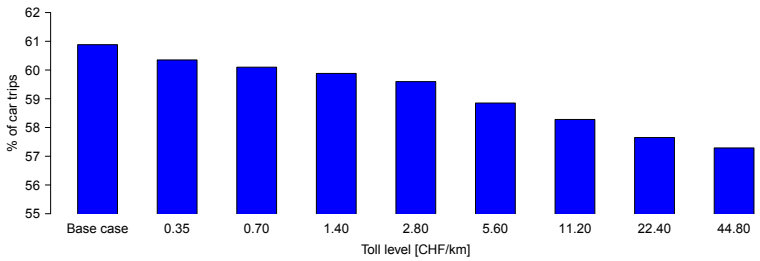


Figure 3.9: Percentage of car trips for the base case and the different toll levels; the remaining trips are PT trips.

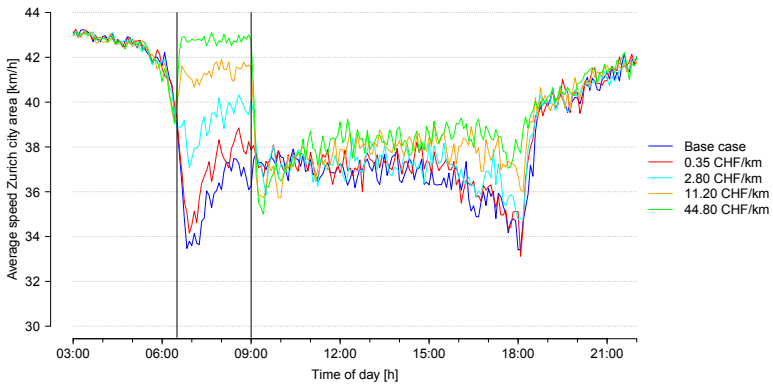


Figure 3.10: Average speed in Zurich city area over time of day for the base case and selected toll levels.

population. For the lowest policy case, average changes in the income deciles range from -0.004 to $+0.012$ *utils* or approximately -0.13 to $+0.39$ *min*, with a slight increase towards higher incomes. For the highest policy case, values range from -0.044 to $+0.012$ *utils* or roughly -1.40 to $+0.39$ *min*, with a stronger increase towards higher incomes. In the average, all but the lowest income decile gain for the lowest policy case, whereas in the highest policy case, only the two highest income deciles gain. In the latter case, all other deciles either lose in terms of time equivalents or almost stay unchanged. As one can see in Fig. 3.12, this observation is also true when converting the utility changes into money terms using individual income equivalents (see Sec. 2.3.3.1), and calculating the average willingness-to-pay (excluding toll payments) for every income decile.

For the highest policy case, and following the time equivalent approach, a compensation of the losers seems not possible: total time gains are not overcompensating total time losses. That is, leaving the toll payments aside, the policy would not be worth the effort from a societal point of view. However, following the income equivalent approach, the willingness-to-pay of the two highest income deciles allows for a compensation of the losers, in particular of the five lowest income deciles. That is, leaving the toll payments aside, the policy would be worth the effort from a societal point of view. This highlights an important implementation problem of policy measures in democratically organized societies: 50% of the population would be better off without the toll, 30% would have an almost unchanged utility level and for only 20% of the population monetized gains appear. This might be an important reason why a majority is likely to refuse the introduction of the policy even though it has an overall positive welfare effect. Moreover, the same might be true for the lowest policy case even though almost all income deciles gain in average: the toll could, however, be perceived as an unequal reallocation of benefits towards higher income groups.

Leaving the toll payments aside for the moment, the blue bars in Fig. 3.13 show the monetized direct utility changes for the eight different toll levels. Following the time equivalent approach (Fig. 3.13(a)), they are calculated by multiplying the utility change of every individual with $\left(\frac{\partial V}{\partial t}\right)^{-1} \approx \frac{1}{\beta_{perf}}$, valuing the result with the average VTTS of the population $\overline{VTTS} = 69.85\ CHF$, and aggregating the results as proposed in Sec. 2.3.3.3. Following the income equivalent approach (Fig. 3.13(b)), they are calculated by applying Eq. 2.13 to the utility changes of every individual, and then aggregating

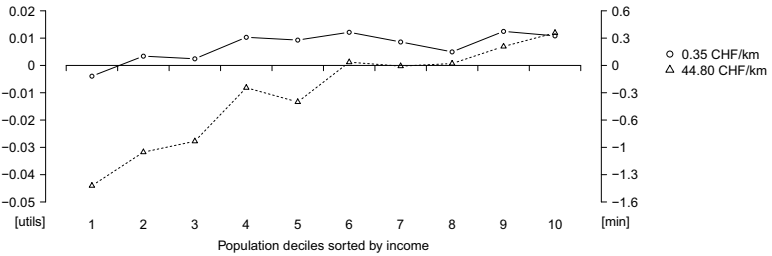


Figure 3.11: Average changes in utility $[utils]$ and approximate time equivalents $[min]$ over deciles of the population, sorted by income. Circles depict a toll level of 0.35 CHF/km, triangles a toll level of 44.80 CHF/km.

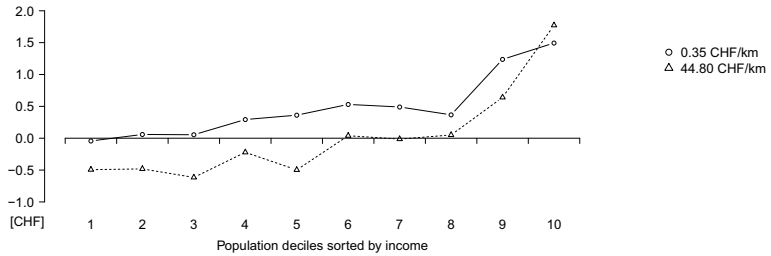
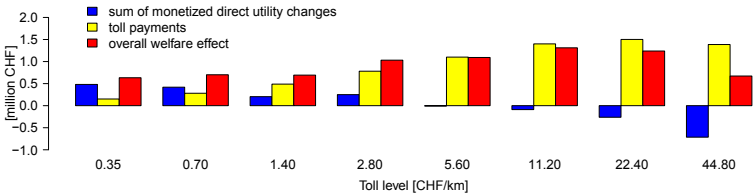
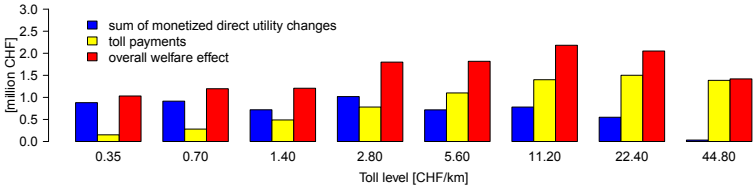


Figure 3.12: Average changes in income equivalents CHF over deciles of the population, sorted by income. Circles depict a toll level of 0.35 CHF/km, triangles a toll level of 44.80 CHF/km.



(a) Monetization via the summation of time equivalents and an average VTTS



(b) Monetization via the summation of income equivalents

Figure 3.13: Different approaches of aggregating and monetizing individual utility changes for all toll levels. Blue bars depict the monetary valuation of direct utility changes, yellow bars indicate the toll payments, and red bars show the overall welfare effect. Results per typical workday and scaled to full population.

the results following Eq. 2.14.

For the time equivalent approach, it can be observed that for toll levels up to 2.80 CHF/km, the blue bars indicate positive values. A toll level of 5.60 CHF/km has almost no effect on the perceived benefits, and all higher toll levels lead to a welfare loss when excluding toll payments in the calculation. In this case, a toll level of 0.35 CHF/km maximizes the perceived benefits. Potentially, there might be even lower toll levels that lead to even higher perceived benefits. When taking the toll payments into account (yellow bars), there is now a positive welfare effect (red bars) for all toll levels since the toll payments overcompensate the perceived welfare losses.

For the income equivalent approach, the sum of monetized direct utility changes is depicted by the blue bars in Fig. 3.13(b), again for the eight different toll levels. In contrast to the time equivalent approach from Fig. 3.13(a), it can be seen that the effect on monetized direct utility

changes stays strictly positive over all toll levels and turns out to be more important. In this case, a toll level of 2.80 CHF/km maximizes the perceived benefits. When adding the toll payments in order to calculate the overall welfare effect, one can notice that the latter naturally stays positive for all toll levels and that the overall welfare effect has a more important amplitude than following the time equivalent approach. For both approaches, a toll level of 11.20 CHF/km maximizes the overall welfare effect.[21]

To sum up, it can be followed that not only the *level* of the welfare effect but even the *sign* of the overall effect might—under certain conditions—depend on the choice between the different approaches of how to monetize and aggregate individual utility changes.

3.6 Discussion

This chapter starts from estimates of individual utility functions based on the estimation of a MNL model. A possible interpretation of this approach is that the utility function is simply a device that helps to construct quantitatively descriptive behavioral models of individuals. In this way, one first constructs and estimates the behavioral model, and then runs a simulation model populated with entities (synthetic persons) using this behavioral model.

The interpretation of the utility as an indicator of individual gains or losses is essentially an afterthought, with no meaning to the simulation results except that random utility modeling has something to do with the individual optimization of utility. Still, the identification of winners and losers seems to be inherently quite robust since it results directly from the behavioral model that is based on surveys or observations. It was also shown that it is possible to quantify individual gains and losses with respect to an individual utility level. General critical issues of this approach enter from different angles, such as:

- Since the MNL model is stochastic, agents are stochastic as well, and some may *de*crease the systematic part of their utility function $V_{i,j}$. These agents are called *logit switchers* in Sec. 3.3. This means that the results cannot be interpreted at the single-agent, single-plan level;

[21] This seems unrealistically high for a real system. It is likely that this has to do with the income that was generated from household data, but is, in this model, applied to individuals. Assuming that a division by two would approximately correct for this issue, then a toll level of 5.60 CHF/km would not seem fully implausible for the city of Zurich, especially if one recalls that this could be offset by a tax reduction.

one either needs to aggregate over subpopulations or calculate the logsum term over all plans of every agent (for an application, see Ch. 5). A different approach to address this issue could be to attach the random components as random but fixed to every alternative of every traveler (see, e.g., Horni et al., 2012).

- One may argue that it is invalid to cast human behavior into an optimization problem at all, and one should rather resort to simple procedural rules.

- Even if individuals' behavior can be cast as an individual optimization problem, it is by no means clear that ex-post happiness is optimized by ex-ante optimization of this descriptive function.

Still, to re-iterate: If one takes into account that one has some random *logit* winners and losers, then the conceptual path leading to the identification of individual winners and losers seems quite straightforward, and might even be sufficient for policy advise as argued by Ahlheim and Rose (1989) (see Sec. 2.3.2).

However, in the context of Benefit-Cost Analysis (BCA), the question whether individual utility changes can somehow be aggregated into some indicator of welfare becomes important. As discussed in Sec. 2.3.3, there are at least two alternatives to do so: the time equivalent approach and the income equivalent approach. Both have been used for presenting the results in the three Case Studies of this chapter. The first approach yields the overall hours of life time that would be generated by the policy change. The second approach yields the overall willingness-to-pay for a policy change. The valuation of time equivalents with individual VTTS leads to the same total benefit as aggregating income equivalents. In that sense, the time equivalent approach can be seen as an intermediate step. However, the intermediate results might be important for policy evaluation and decision making, and they would possibly not appear when using the income equivalent approach. One could also argue that an evaluation of projects would be possible where the decision variable is the number of equivalent hours of life time that are generated per unit of money invested.

At any rate, the comparison of the results in time equivalents (Fig. 3.6 and Fig. 3.11) to income equivalents (Fig. 3.7 and Fig. 3.12) makes clear that the selection of the aggregation procedure can lead to quite different equity interpretations:

In Case Study II, Fig. 3.6 shows that time equivalents lead to similar gains across all income groups. The willingness-to-pay, sorted by income group in Fig. 3.7, implies that high income groups would have a disproportionately high willingness-to-pay for the PT speed increase. This is, in fact, quite intuitive: Higher income groups have a disproportionately high willingness-to-pay for good schools, a good health system or a good transport system. In this sense, a progressive income tax following the principle of equal sacrifice (Mitra and Ok, 1997; Young, 1990) may not even be re-distributive with respect to such types of government expenses, since just reflects the individual willingness-to-pay for improving the corresponding services.[22]

In Case Study III, Fig. 3.11 shows for the highest policy case that large losses incur for 50% of the population with the lowest incomes. The time gains of the top 20% of the population do not compensate for that. By using the willingness-to-pay in Fig. 3.12, this picture changes and the income equivalents of the top 20% overcompensate those of the 50% with the lowest incomes. In that sense, road user pricing schemes might have regressive impacts on the welfare distribution of society. This highlights a structural issue which should be considered when evaluating transport policies. The comparison between the income equivalent and the time equivalent approach might help to understand reasons for low public acceptance. It might even help to find an indicator of how to improve the acceptance of unpopular projects. The general problem is quite obvious: Financing infrastructure projects by non-differentiated user fees leads to a regressive reallocation of welfare towards higher income groups. Financing projects by a progressive income tax or by price differentiation might be more appropriate. Provided this tax has been set up for reallocating resources towards lower income groups, then it would have to be even more progressive than the welfare reallocation towards higher income groups by the transport projects. One possibility to address these issues might be the design of *policy packages* where policies are directly coupled with a redistribution scheme, e.g. of the toll payments. Using an agent-based approach, this seems feasible since it is possible to perform the analysis on every desired level of disaggregation, e.g. by combining multiple demographic attributes and considering the geo-spatial distribution of winners and losers (see later in Ch. 5.4.2). This could help to design policy packages that meet broader public acceptance.

[22] Clearly, this is only true if the higher income groups are not operating in a separate system, such as private schools, private health insurance, or private transport systems.

Furthermore, the use of time equivalents for valuing user benefits additionally opens the possibility to follow Mackie and Worlsley (2013) to use behavioral information for modeling, but standard values per minute across incomes, modes and regions. A comparison of that approach using an average VTTS to the income equivalent approach was performed in Case Study III for finding the optimal toll level of a morning peak distance toll in Zurich, Switzerland. The results indicate that the choice between the two aggregation and monetization approaches changes the level of the estimated welfare gains, but also the sign of the overall welfare effect might not be stable.

To sum up, it is important to note that the different attempts of measuring welfare from above rely on exactly the same description of human behavior. This highlights that the model predicting the system's reaction to a policy change can be seen as independent from the different interpretations of measuring welfare.

3.7 Summary

Standard BCA requires some monetization of positive and negative effects that might result from transport policies under consideration. A policy is usually recommended if the monetized aggregated economic benefit outweighs the monetary costs. Effects on individuals or subgroups of the population are rarely investigated, even though this would provide valuable insights into problems that are linked to the public acceptance of the policy.

This chapter proposed how the standard approach could be improved in practice by using multi-agent simulations that are capable to provide better information for policy makers. The chapter aimed at directly linking the standard approach of valuing user benefits to the understanding of implementation problems when assuming income-dependent behavior in the choice model, and multiple choice dimensions simultaneously.

Therefore, individual income-dependent utility functions were estimated from survey data, assuming a continuously increasing VTTS with increasing income. In three Case Studies, the impacts of a non-monetary policy and of a monetary policy on travelers' behavior as well as on individual utility levels were investigated. Finally, these individual utility changes were aggregated and monetized via the income equivalent and the time equivalent approach from Sec. 2.3.3.2, in order to identify problems linked to public acceptance of the policies. Three important findings could be retained: First, it was

shown that the simulation of changes in human mobility behavior as a reaction to transport policies becomes more realistic by using estimations of individual utility functions that are based on survey data. Second, using the resulting individual utility differences to identify winners and losers seems a quite robust procedure. Third, the results of this chapter indicate that an aggregation and/or monetization of these utility differences in order to derive an indicator of welfare change raises the question about the aggregation procedure:

For the use of income equivalents, Case Study III points out that road user pricing might have regressive impacts on the welfare distribution of society. Interestingly, the same is true for the non-monetary PT speed increase in Case Study II. A progressive (income) tax might therefore not be re-distributive since it only reflects the willingness-to-pay of, e.g., the corresponding income decile. For these reasons, the use of time equivalents in project appraisal was discussed, relying on the same description of human behavior given by the estimated utility functions. Applying both, the income equivalent and the time equivalent approach to a parametric optimization of a distance toll in Case Study III leads to different levels of the overall welfare change. Importantly, even the sign of the overall welfare change might not be stable when combining the time equivalent approach with a valuation via an average VTTS. It is therefore important to note that these two approaches yield different equity interpretations and that a comparison could help designing projects with broader public acceptance.

Overall, the results demonstrate that a better understanding of problems linked to public acceptance can be achieved by including individual income into utility calculations. A rather practical contribution of this work is the following: up until now, the literature in this field of agent heterogeneity only studied rather limited scenarios of a corridor (van den Berg, 2011), simple networks (Zhang et al., 2008), or more complex networks but only allowing for one choice dimension (Franklin, 2006). The present chapter, however, showed that the welfare computations can also be done for heterogeneous agents that have multiple choice dimensions available.

Chapter 4

Heterogeneity in User Attributes

4.1 Introduction

The chapter starts from the assumption that car user costs are about to increase in the upcoming decades. This is likely to have impacts on aggregated air pollutant emissions and on the spatial distribution of emissions. The concentration of some air pollutants still exceeds the limiting values prescribed by the European Union, especially in urban areas. Thus, the main focus of this chapter is the question whether a decrease in car travel demand due to higher user costs would result in a over-proportional reduction of air pollutant emissions. When it comes to the discussion of cost-related transport policies, large-scale transport models are needed. However, for the analysis of air pollutant emissions, a detailed investigation of the micro-level is also necessary. In order to combine both objectives, a multi-agent transport model is used for simulations. The Multi-Agent Transport Simulation (MATSim) is able to simulate large-scale scenarios. It is also particularly suitable for calculating air pollutant emissions on a detailed level as complete daily plans are modeled and the traveler's identity is kept throughout the simulation process. For illustration purposes of the impacts on air pollutant emissions, Nitrogen Dioxide (NO_2) is chosen. Furthermore, the transport sector is the main source of NO_2 emissions and NO_2 concentration limits are often still exceeded.

The content of this chapter is an edited version of Kickhöfer et al. (2013). The chapter forms the basis for answering Research Questions 3 and 4. The remainder of the chapter is organized as follows: it starts with a presentation of the transport model in Sec. 4.2.1, followed by a description

of the Emission Modeling Tool in Sec. 4.2.2. Sec. 4.3 consists of three parts: first, a presentation of the Munich base scenario; second, a description of the simulation approach and a definition of four policy scenarios; and third, the validation of the base scenario with respect to modal split and traffic volumes. In Sec. 4.4, aggregated car user price elasticities of different subpopulations (inner-urban traffic, commuter, and reverse commuter) are calculated and discussed. Furthermore, car travel demand as well as NO_2 emissions are analyzed on a spatially disaggregated level for all scenarios. The chapter ends with a summary in Sec 4.5.

4.2 Methodology

This section (i) gives a brief overview of the general simulation approach of MATSim along with the model specifications relevant for this chapter, and (ii) shortly describes the Emission Modeling Tool.

4.2.1 Transport Simulation with MATSim

4.2.1.1 Overview

In the following, only general ideas about the transport simulation with MATSim are presented. For in-depth information about the simulation framework, please refer to Raney and Nagel (2006), or to Sec. 2.2.1, respectively.

In MATSim, each traveler of the real system is modeled as an individual agent. The modeling approach consists of an iterative loop which is composed of the following steps:

1. *Generating Plans*: All agents independently generate daily plans that encode among other things their desired activities during a typical working day as well as the transport mode for every intervening trip. One of these plans is marked as 'selected'.

2. *Simulating Mobility*: All selected plans are simultaneously executed in the simulation of the physical system.

3. *Evaluating Plans*: All executed plans are evaluated by a utility function which typically encodes the attributes travel time and monetary cost, as well as the perception of these attributes. The attributes typically vary within the available choice dimensions (route, mode, time, etc.).

4. *Learning*: Some agents obtain new plans for the next iteration by modifying copies of existing plans. This modification is done by several modules, one for every available choice dimension. The choice between plans is performed with respect to a Multinomial Logit (MNL) model where the total utility of all plans in the choice set enters.

The steps 'Generating Plans', 'Evaluating Plans', and 'Learning' represent the mental layer of the model which is needed for behavioral modeling. 'Simulating Mobility' exhibits the physical layer of the model which is needed to capture interaction between agents in a (capacity) constraint environment. The repetition of the iteration cycle coupled with the agent database enables the agents to improve their plans over many iterations. This is why it is also called learning mechanism. The iteration cycle continues until the system has reached a stable outcome.

4.2.1.2 Model Specifications

Choice Dimensions For the mental layer within MATSim which describes the behavioral learning of agents, a utility based approach is used in this chapter. When choosing between different options with respect to a MNL model (see Sec. 2.2.1.4), agents are allowed to adjust their behavior among two choice dimensions: route choice and mode choice[1]. The former allows individuals to adapt their routes on the road network when going by car. The latter makes it possible to change the transport mode for a sub-tour within the agent's daily plan. Only a switch from car to public transit or the other way around is possible. Trips that are initially done by any other mode remain fixed within the learning cycle. From a research point of view, this approach can be seen as defining a system where public transit is a placeholder for all substitutes of the car mode.

Behavioral Parameters The utility functions used in this chapter are identical to those described in Sec. 2.2.1.3. Following Eq. 2.1, there is a positive utility earned by performing activities which is described by a logarithmic form in Eq. 2.2. Additionally, the travel related part (see Eq. 2.3) considers travel times and monetary costs as attributes of every car and public transit trip. No late penalty applies since this chapter investigates a real-world scenario. Due to a lack of behavioral parameters

[1] In this chapter, car ownership is modeled on a household basis. However, there is no vehicle assignment module which takes into account intra-household decision making. Thus, it might happen that the same car is assigned to two or more agents of the same household at the same time.

Table 4.1: Estimated and adjusted utility parameters; resulting VTTS.

(a) Kickhöfer (2009)

$\hat{\beta}_{tr,car}$	-2.26	$[\frac{utils}{h}]$
$\hat{\beta}_{tr,pt}$	-2.36	$[\frac{utils}{h}]$
$\hat{\beta}_{c,car}$	-0.20	$[\frac{utils}{mU}]$
$\hat{\beta}_{c,pt}$	-0.0535	$[\frac{utils}{mU}]$
$\hat{\beta}_{perf}$	N/A	$[\frac{utils}{h}]$
$VTTS_{car}$	$+11.30$	$[\frac{mU}{h}]$
$VTTS_{pt}$	$+44.11$	$[\frac{mU}{h}]$

(b) MATSim

$\beta_{tr,car}$	-0.00	$[\frac{utils}{h}]$
$\beta_{tr,pt}$	-0.10	$[\frac{utils}{h}]$
$\beta_{c,car}$	-0.20	$[\frac{utils}{mU}]$
$\beta_{c,pt}$	-0.0535	$[\frac{utils}{mU}]$
β_{perf}	$+2.26$	$[\frac{utils}{h}]$
$VTTS_{car}$	$+11.30$	$[\frac{mU}{h}]$
$VTTS_{pt}$	$+44.11$	$[\frac{mU}{h}]$

for the municipality of Munich, estimated parameters[2] are taken from a linear model in Kickhöfer (2009) who based the estimations on data from Switzerland provided by Vrtic et al. (2008); these parameters are shown in Tab. 4.1(a), together with the corresponding Value of Travel Time Savings (VTTS). Splitting the time related parameters into opportunity costs of time and additional disutility caused by traveling (for details, see Sec. 2.2.1.3) leads to the parameters used in the simulation, depicted in Tab. 4.1(b). Please note that this adjustment does not change the VTTS as a comparison of the two tables shows. Also note, that the cost related parameters $\beta_{c,car}$ and $\beta_{c,pt}$ are different for the two transport modes.[3] This is typically found when estimating behavioral parameters from survey data. The modeler should, whenever possible, not limit the estimation model with respect to this degree of freedom.[4] The Alternative Specific Constant (ASC) β_0 is not estimated significantly different from zero. It is, therefore, not considered in the functional form of the utility functions. This essentially means that no general a-priori preference for one of the transport modes can be found in the data. Because of the argument regarding the opportunity cost of foregone activity time when arriving early (see Sec. 2.2.1.3), the *effective* marginal disutility of early arrival is $\beta_{early_{eff}} = -\beta_{perf} \cdot t_{*,i}/t_{perf,i} \approx -\beta_{perf} = -2.26/h$ which is equal to the *effective* marginal disutility of traveling with car $\beta_{tr,car_{eff}}$. The *effective*

[2] Estimated parameters are in this chapter flagged by a hat.
[3] For an interpretation of this estimation result and its limitations, please see Sec. 2.3.
[4] Limiting the model to a uniform value of β_c is in some cases needed for economic evaluation. However, this would omit some information that is present in the data; for a discussion on this topic, see Sec. 2.3.3.3.

marginal disutility of traveling by Public Transport (PT) is, by the same argument, $\beta_{tr,pt_{eff}} = -\beta_{perf} \cdot t_{*,i}/t_{perf,i} + \beta_{tr,pt} \approx -\beta_{perf} + \beta_{tr,pt} \approx -2.36/h$.

As a result of this model specification, it is now possible to observe user reactions to price increases and to derive the corresponding price elasticities of demand.

4.2.2 Emission Modeling Tool

The Emission Modeling Tool was developed and tested by Hülsmann et al. (2011) and was further improved by Kickhöfer et al. (2013). For detailed information, please refer to Sec. 2.2.2.

The tool links MATSim to the Handbook on Emission Factors for Road Transport (HBEFA) database, and essentially calculates warm and cold-start emissions for private cars and freight vehicles. The former emissions are emitted when the vehicle's engine is already warmed whereas the latter occur during the warm-up phase. In the present model, warm emissions differ with respect to vehicle characteristics, traffic state, and road type. Cold-start emissions differ with respect to vehicle characteristics, accumulated distance, and parking duration.

In a first step, vehicle characteristics are obtained from survey data and typically comprise vehicle type, age, cubic capacity and fuel type. They are then used for very differentiated emission calculations. Where no detailed vehicle information is available, fleet averages for Germany are used. For the calculation of warm emissions, MATSim traffic dynamics are mapped to two HBEFA traffic states: free flow and stop&go. In order to identify road types, information from network data is mapped to HBEFA road types, such as motorway, trunk road, distributor road, or tertiary road. For the calculation of cold-start emissions, parking duration and accumulated distance monitored in the simulation. The handbook then provides emission factors for all relevant pollutants differentiated among the characteristics presented above.

In a second step, so-called 'emission events' are generated based on these warm and cold emission factors. The events provide information about person, time, link, and absolute emitted values by emission type. The definition of emission events follows the MATSim framework that uses events for storing disaggregated information as objects in JAVA programming language and as XML in output files. Emission event objects can be accessed during the simulation or generated later on in a post-processing of

the standard MATSim events.

4.3 Case Study IV: Rising Car User Costs—Munich, Germany

The methodology described in Sec. 4.2 is now applied to a large-scale scenario of the Munich metropolitan area with about two million individuals. For this purpose, a scenario needs to be set up based on network and survey data. The process is described in Sec. 4.3.1, followed by a specification of the simulation procedure in Sec. 4.3.2 and a validation in Sec. 4.3.3 where it is discussed to what extent the simulation reproduces reality.

4.3.1 Scenario Setup

Network Network data was provided by the municipality of Munich (RSB, 2005). The data matches the format of the aggregated static transport planning tool Verkehr In Städten – UMlegung (VISUM). It represents the road network of the federal state Bavaria, being more detailed in and around the city of Munich and less detailed further away. It consists of 92'259 nodes and 222'502 connecting edges (= links). Most road attributes, such as free speed, capacity, number of lanes, etc. are defined by the road type. Only geographical position and length are attributes of each single link. This data is converted to MATSim format by taking length, free speed, capacity, number of lanes, and road type from VISUM data. VISUM road capacities are meant for 24-hour origin-destination matrices. Since the network is almost empty during night hours, peak hour capacity is set to VISUM capacity divided by 16 (not 24). This results in an hourly capacity of about 2000 vehicles per lane on an urban motorway. In order to speed up computation, some road categories corresponding to small local roads are removed from the network. Furthermore, nodes with only one ingoing and one outgoing link are removed. The two resulting links are then merged, bringing the size of the network down to 17'888 nodes and 41'942 links. When merging, the two link lengths are summed up; free speed is calculated based on the minimal time needed for passing the original links; capacity is set to the minimum of the two links; the number of lanes is calculated based on the number of vehicles that fit on the two original links; and finally the road type – important input for emission calculations – is set to the one of the outgoing link.

Population In order to obtain a realistic time-dependent travel demand, several data sources are converted into the MATSim population format. The level of detail of the resulting individual daily plans naturally depends on the information available from either disaggregated Stated Preference data or aggregated population statistics. Therefore, *three subpopulations* are created, each corresponding to one of the three different data sources:

- Inner-urban Traffic (based on Follmer et al. (2004)):
  The synthetic population of Munich is created on the basis of very detailed survey data provided by the municipality of Munich RSB (2005), named Mobility in Germany (MiD 2002). In the area of the Munich municipality, 3612 households (with 7206 individuals) were interviewed. The data consists of different data sets such as household data, person specific data and trip data. A detailed description of survey methods and data structure can be found in Follmer et al. (2004). Individuals were asked to report their activities during a complete day including activity locations, activity start and end times as well as the transport mode for the intervening trips. Due to privacy protection, not the exact coordinates of activity locations are available, but only the corresponding traffic analysis zones (1066 zones in total). For the generation of the synthetic MATSim population, individual activity locations are distributed randomly within these zones. Furthermore, all incomplete data sets are removed, e.g. when the location or the starting times of one activity is missing in the survey. The transport modes train and bus are treated as public transport trips, motorbikes and mopeds are treated as car trips. The transport modes ride (= in car as passenger), bike and other (= unknown) are kept for the initial MATSim population. Overall, the data cleaning results in 3957 individuals, the representative sample for demand generation. Finally, these agents are *cloned* while holding activity transport analysis zones constant but finding new random locations within these zones for every clone. This process is performed until the population reaches the real-world size of 1.4 million inhabitants. Thus, the synthetic population living inside the Munich municipality boundaries consists for this study of 1'424'520 individuals. MiD 2002 also provides detailed vehicle information for every household. Linking this data with individuals makes it possible to assign a vehicle to a person's car trip and thus, calculating emissions based on this detailed information. As of now there is, however, no vehicle assignment

module which models intra-household decision making. It is, therefore, possible that a vehicle is assigned to more than one person at the same time.

- Commuter Traffic (based on Böhme and Eigenmüller (2006)):
  Unfortunately, the detailed data for the municipality of Munich does neither contain information about commuters living outside of Munich and working in Munich nor about people living in Munich and working outside of Munich. The data analyzed by Böhme and Eigenmüller (2006) provides information about workers that are subject to the social insurance contribution with the base year 2004. Origin and destination zones are classified corresponding to the European Nomenclature of Statistical Territorial Units (NUTS), level 3. Thus, the origin-destination flows between Munich and all other municipalities in Germany are available. Neither departure times nor transportation mode are, however, provided. The total number of commuters tends to be underestimated since public servants and education trips are not included in this statistic. Therefore, every origin-destination relation is increased by the factor 1.29 (Guth et al., 2011). Initially, car trips are assumed to 67% of the total commuter trips, public transport to 33% (MVV, 2007). Departure times are set so that people arrive at their working place, according to a normal distribution with $N(8{:}00 \text{ a.m.}, 2\ h)$ when routed on an empty network. Work end times are set to nine hours after the arrival at the working place. This results overall in 510'150 commuters from which 306'160 people have their working place in Munich. All these MATSim agents perform a daily plan that encodes two trips: from their home location to work and back. Due to this simplification, they are the first contribution to *background traffic*, as it will be addressed from here on.

- Commercial Traffic (based on ITP and BVU (2007)):
  The second contribution to *background traffic* is given by commercial traffic with the base year 2004. On behalf of the German Ministry of Transport, ITP and BVU (2007) published the origin-destination commodity flows throughout Germany differentiated by mode and ten groups of commodities. Origin and destination zones inside Germany are classified corresponding to NUTS 2, and outside Germany to NUTS 3 level, respectively. The number of trucks (> 3.5 tons) between two zones or within a zone is calculated based on the commodity

flow in tons and the average loading of trucks.[5] The starting and ending points of the trips are—due to the lack of more detailed data—randomly distributed inside the origin and destination zone, respectively. The resulting MATSim agents obtain a plan that only consists of two activities with one intervening trip. Departure times are set so that the number of *en-route vehicles* in the simulation matches a standard daily trend for freight vehicles.[5] For this scenario, trips are only considered if they are carried out at least once in Bavaria during the day. This results in 158'860 agents with one single commercial traffic trip.[6]

Overall, the synthetic population consists of 2'093'530 agents. For background traffic, no detailed vehicle information is available. Emissions are, therefore, calculated with the help of fleet averages for cars and trucks from HBEFA.

4.3.2 Policy Design and Simulation Procedure

Policy Design The policies that will be analyzed in this chapter are the following:

- Base case: car user costs remain constant (see below)
- Policy case 1: increasing car user costs by 25% to 12.5 ct/km
- Policy case 2: increasing car user costs by 50% to 15 ct/km
- Policy case 3: increasing car user costs by 75% to 17.5 ct/km
- Policy case 4: increasing car user costs by 100% to 20 ct/km

User costs[7] for car are set to 10 ct/km in the base case, but vary for the different policy cases (see above). User costs for public transport are assumed to be constant at 17 ct/km for all policy cases.

[5] Estimations are based on personal communication with G. Liedtke.

[6] Kickhöfer and Nagel (2013) state that "[t]his is a rather simple approach of generating freight traffic which is due to the fact that, in the literature, modeling freight transport has not gained as much attention as passenger transport. However, there is growing interest in this field since the movement of commodities is increasing, and with it the importance of better behavioral modeling of firms and their decision making. For example, Giuliano et al. (2010) base their estimations of freight flows on online sources in order to assure a maximum of transferability and automatic updating. For a new approach of how to model freight transport in the MATSim framework, please refer to Schröder et al. (2012)".

[7] Please note that the term 'user costs' is referred to as out-of-pocket costs for the users.

Simulation Procedure To speed up computations, a random 10% sample is used in the subsequent simulations; other studies indicate that this seems to be an appropriate percentage in order to achieve results close enough to reality (see, e.g., Chen et al., 2008). For choosing between travel alternatives, the re-planning modules RCM and MCMb) from Sec. 2.2.1.4 are used. The car traffic flow simulation and the simulation of other modes follow the description in Sec. 2.2.1.2. That is, travel times for PT are approximated by multiplying free flow car travel times by a factor of 2.0. For the base case, the simulation is set up as follows:

- For 800 iterations, 15% of the agents perform route adaptation, 15% change the transport mode for a car or PT sub-tour in their daily plan, and 70% switch between their existing plans according to Eq. 2.5.
- Between iteration 801 and 1000, route and mode adaptation is switched off; in consequence, agents only switch between existing options according to Eq. 2.5.

The output of iteration 1000 is then used as input for the continuation of the base case and the four different policy cases. All simulation runs are continued for another 500 iterations. Again, during the first 400 iterations 15% of the agents perform route adaption while another 15% of agents choose between car and public transport for one of their sub-tours. The remaining agents switch between existing plans. For the final 100 iterations only a fixed choice set is available for all agents. When evaluating the impact of the car user cost increases, the final iteration 1500 of every policy case is compared to iteration 1500 of the base case. Emissions are calculated for iteration 1500 of all cases. Public transit is in the present chapter assumed to run emission free; it is therefore a placeholder for all environmentally friendly transport modes. PT travelers are teleported between activity locations with free flow car travel times multiplied by a factor of 2.0 (see Sec. 2.2.1.2).

4.3.3 Validation of the Base Case

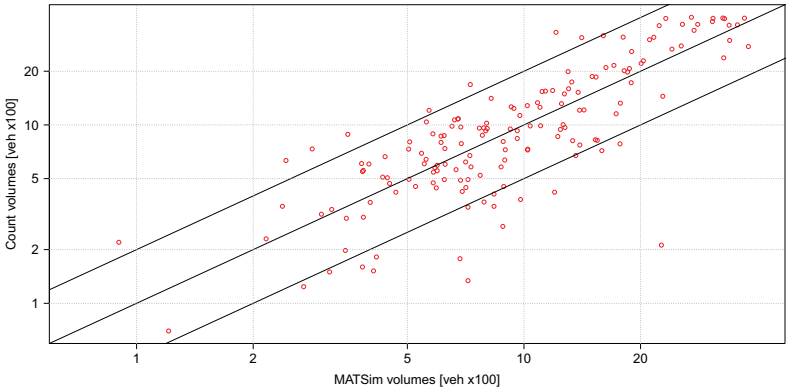
Modal Split While converting the input data described by Follmer et al., 2004 into the MATSim synthetic population (see Sec. 4.3.1), some individuals were omitted because of a lack of coordinates or activity times. Therefore, Tab. 4.2 shows differences in the modal split over all trips comparing the input data with the synthetic subpopulation at iteration 0

Table 4.2: Trips per transport mode as percentage of total trips; Comparison between input data (Follmer et al., 2004) and synthetic urban travelers in the simulation.

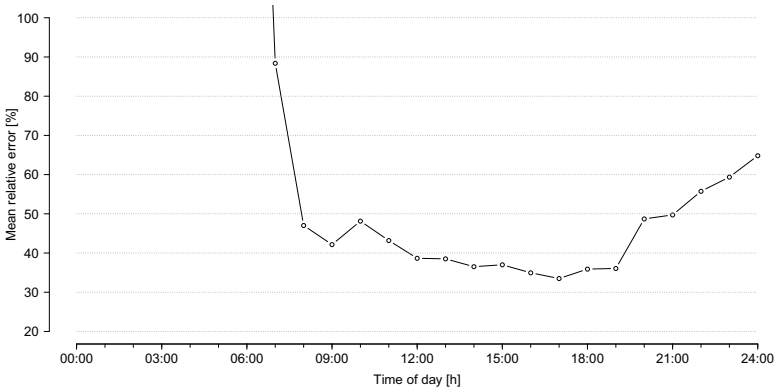
Mode	Follmer et al. (2004)	Synthetic trav. it.0	Synthetic trav. it.1500	Δ it.0	Δ it.1500
bike	10	12.05	12.05	+2.05	+2.05
car	26	22.48	20.88	−3.52	−5.12
PT	22	21.98	23.59	−0.02	+1.59
ride	13	11.39	11.39	−1.61	−1.61
undef.	0	0.55	0.55	+0.55	+0.55
walk	29	31.55	31.55	+2.55	+2.55

and 1500. Note that only the mode share of the subpopulation traveling within Munich is shown. As one can see, the initial synthetic population contains 2.55% more walk trips and 2.05% more bike trips than the input data. In contrast, it contains 3.52% less car trips and 1.61% less ride trips. Public transport trips remain almost unchanged and the unknown mode is not discussed further because of the small number of trips. The error seems to be acceptable since no major differences occur. When the system is in a relaxed state (it.1500), there are even less car trips, but more public transport trips than in the input data. Reasons might be the missing location choice module and the assumptions regarding the specification of the utility function. Overall, the additional increase in public transport and decrease in car trips amounts only to 1.6%. Thus, the synthetic MATSim population seems to be a good starting point for analyzing the change in travel demand and air pollutant emissions resulting from rising car user costs.

Comparison to Counting Stations Before analyzing demand and emission reductions, the realism of traffic flows in the base case is validated here. As described in Sec. 4.2.1, the interaction of individuals on the physical representation of the road network is simulated over 1500 iterations. After reaching a stable outcome, count data is used to determine the quality of the simulation output. For the Munich region, data from 166 traffic counting stations is aggregated for every hour over time of day. The best quality of this data is available for Thursday, January 10th 2008. It is now used to compare simulated traffic volumes to real-world values. Fig. 4.1(a) depicts the comparison for one hour and all counting stations. If all data



(a) Comparison for one hour (2:00 p.m. to 3:00 p.m.)



(b) Mean relative error over time of day

Figure 4.1: Realism of the simulation at iteration 1500. For the Munich municipality area, 166 traffic counting stations provide real-world traffic counts for validation.

points were on a 45 degree line, the simulation would perfectly reproduce real traffic volumes. However, as one can see, there are errors between simulated and real values. The mean relative error for every sensor is a good indicator for the overall fit of the simulation. It is calculated by:

$$MRE = \left| \frac{q_{sim} - q_{real}}{q_{real}} \right|, \tag{4.1}$$

where q_{sim} indicates the simulated and q_{real} the real-world vehicle flow over the corresponding counting station in the corresponding hour. Averages for a given hour are obtained by averaging over all sensors. In the example shown in Fig. 4.1(b), the simulation deviates strongly from reality during night hours, i.e. from midnight until 7:00 a.m. During daytime, i.e. from 7:00 a.m. until the evening, the hourly mean relative error is between 30% and 50% with better values in the afternoon.

In order to reach this accuracy, there was need for some adjustments , e.g. varying the parameters of the normal distribution that describe work arrival time peak and variance for commuters (see Sec. 4.3.1). For now, since this is meant to be a research scenario, the quality of the simulations seems to be adequate. However, by further optimizing travel demand and network information, better values for the mean relative error can be obtained as Chen et al. (2008) or Flötteröd et al. (2011) showed for a scenario of Zurich, Switzerland.

4.4 Results

This section aims at investigating two research questions: (i) *Are price elasticities of emissions higher than those for car travel demand?*, and if yes, (ii) *Can a spatial effect be observed?*. In Sec. 4.4.1, overall price elasticities of car travel demand are derived from the simulation and then compared these to price elasticities of NO_2 emissions. In Sec. 4.4.2, areas with high travel demand in the city of Munich are identified by using a more disaggregated approach. In a second step, a spatial analysis of absolute changes in demand and NO_2 emissions resulting from policy case 4 is conducted. Then, the role of absolute changes in emissions per vehicle kilometer is investigated, following the same spatial analysis.

4.4.1 Aggregated Price Elasticities

Possible reactions of car users to increasing distance costs comprise, in the present chapter, either choosing shorter but eventually more time consuming routes or changing the transport mode to public transport, the placeholder for all substitutes to car.

Fig. 4.2 shows the daily demand for vehicle kilometers traveled (vkm) over different distance cost factors (from 10 ct/km for the base case up to 20 ct/km for the highest policy case). The reduction in demand is presented for all subpopulations (see Sec. 4.3.1): black circles correspond to inner-urban traffic, red triangles and green crosses to commuters and reverse commuters, respectively, and blue crosses to freight traffic. The inner-urban demand for vehicle kilometers traveled drops from about 400'000 vkm in the base case by 18% to roughly 333'000 vkm in the highest policy case. Car travel demand drops more strongly for commuters and reverse commuters from 4'624'000 vkm by 72% to 1'290'000 vkm, and from 1'650'000 vkm by 54% to 754'000 vkm, respectively. The big difference between inner-urban demand and (reverse) commuters results from the much longer distances traveled by the last two groups where the car mode gets extremely unattractive. Travel demand reactions for freight traffic remains almost unchanged since it can only change to shorter routes but not change the transport mode. The figure also provides linear regression lines including their functional forms for every subpopulation. Even though, especially for commuter traffic, a linear regression obviously does not lead to the best fit (one can nicely see the "inverse-S-shape" produced by the MNL model), it is still quite appropriate in order to derive constant price elasticities.

Choosing $p_0 = 10$ ct/km as operating point, price elasticities of demand can directly be derived for every policy case i, using:

$$\eta_{q,p} = \frac{\frac{q_i - q_0}{q_0}}{\frac{p_i - p_0}{p_0}} \ , \tag{4.2}$$

where q_i is the travel demand at price level p_i. In order to describe the overall relationship between user costs and car travel demand, a constant price elasticity can be derived using the regression functions:

$$\eta_{q,p} = \frac{dq}{dp} \cdot \frac{p_0}{\hat{q_0}} \ , \tag{4.3}$$

where $\frac{dq}{dp}$ is the gradient of the corresponding regression function and $\hat{q_0}$

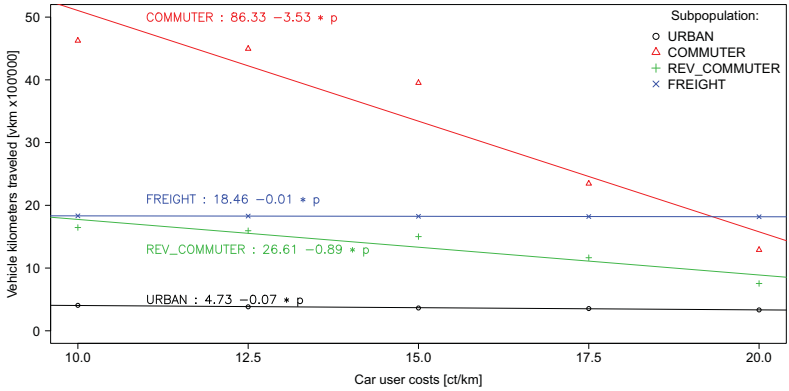


Figure 4.2: Overall daily *vehicle kilometers traveled* for the base case and the four policy cases by subpopulation: simulated values and estimations as linear regression functions; values for a representative 10% sample.

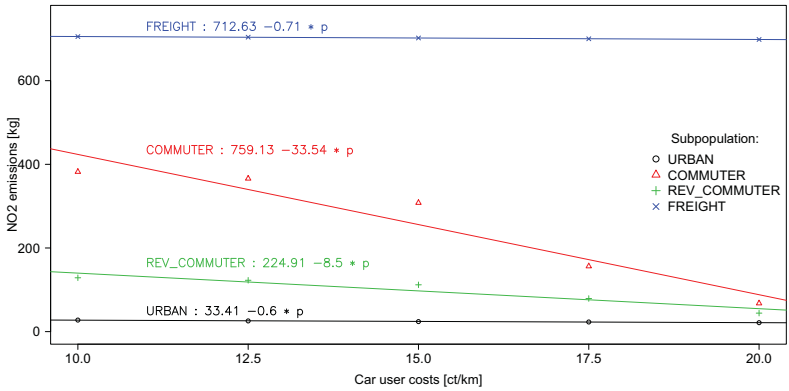


Figure 4.3: Overall daily NO_2 emissions in kilograms for the base case and the four policy cases by subpopulation: simulated values and estimations as linear regression functions; values for a representative 10% sample.

is the estimated initial demand for car trips at $p_0 = 10\ ct/km$. Applying Eq. 4.3 to the three subpopulations, that are affected by the policy, leads to the following estimated constant price elasticities of car travel demand:

$$\hat{\eta}_{q,p}^{Urban} = -0.173\,, \qquad \hat{\eta}_{q,p}^{Commuter} = -0.692\,, \qquad \hat{\eta}_{q,p}^{Rev.Commuter} = -0.502\,.$$

These estimations indicate that e.g. a car user cost increase of 10% (at the operating point $p_0 = 10\ ct/km$) leads to a reduction in car trips by 1.73% for inner-urban traffic, by 6.92% for commuter traffic, and by 5.02% for reverse commuters. Graham and Glaister (2002) present a wide range of fuel price elasticities collected from different studies. When summarizing the different studies, the authors find short-term fuel price elasticities in the range from −0.2 to −0.5, for Germany around −0.45. However, the range within Germany goes from −0.25 to −0.86. The fuel price elasticities found in the present chapter are somewhat smaller for inner-urban traffic and within the range for reverse commuter and commuter. Obviously, introducing more choice dimensions into the model, such as location choice or the possibility of dropping activities, is likely to influence the results. At this point, it can be stated that, overall, the model produces reasonable behavioral reactions to car user price increases.

Similarly to Fig. 4.2, overall NO_2 emissions are shown in Fig. 4.3, again for the base case and the four policy cases. Linear regression lines and functional form are also provided. As expected, NO_2 emissions decrease for all subpopulations, again more strongly for commuters and reverse commuters than for inner-urban traffic. Freight traffic has the most important impact on overall emissions, and their level is barely influenced by the car user price increase. Again, this is due to the fact that freight demand is not allowed to change the transport mode. Only a small reduction can be observed, resulting from shorter distances chosen by the router module. Equally to the price elasticities of demand, price elasticities of NO_2 emissions are calculated to:

$$\hat{\epsilon}_{q,p}^{Urban} = -0.219\,, \qquad \hat{\epsilon}_{q,p}^{Commuter} = -0.792\,, \qquad \hat{\epsilon}_{q,p}^{Rev.Commuter} = -0.608\,.$$

The price elasticities are found to be roughly the same for other exhaust emission types under consideration (e.g. PM or SO_2). When comparing them to the price elasticities of car travel demand from above, one can notice a higher elasticity of emissions than of demand for all subpopulations.

Thus, an increase in car user costs leads to a higher reduction in emissions than in demand. Two explanations come to mind:

1. *Biased mode switch effect*: An over-proportional fraction of travelers who performed long car trips with high speed levels now change from car to public transport. This mainly affects commuters and reverse commuters when driving outside of Munich.

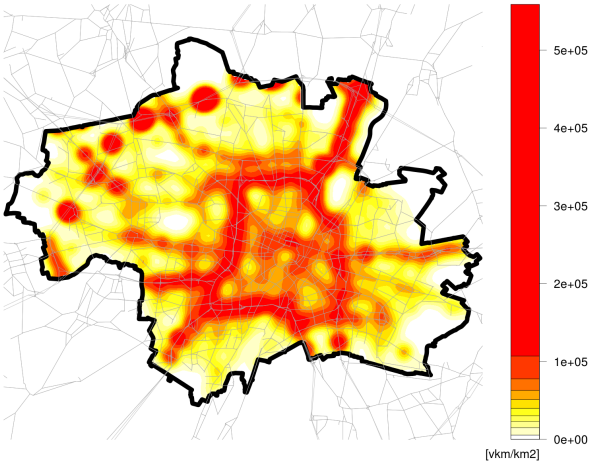
2. *Congestion relief effect*: Travelers are driving faster on formerly congested roads. This presumably applies for inner-urban travelers, but also for the other subpopulations when driving inside Munich.

Both explanations are based on the fact that emission levels are usually the lowest for speed levels around 60 km/h (see, e.g., Maibach et al., 2008, p.58). Emissions per vehicle kilometer increase for lower but also for higher speed levels, forming an *U-shaped* function with its minimum around 60 km/h. That is, when mainly trips with high speed levels are reduced (in this case by changing to another mode), overall emissions drop more than demand. The same is true when traffic flow becomes more fluid on formerly congested roads. It seems that the second effect can be observed since the model includes spillback effects, different traffic states, and individual vehicle characteristics. The following section will address this hypothesis by looking at spatial patterns of changes in travel demand and in air pollutant emissions.

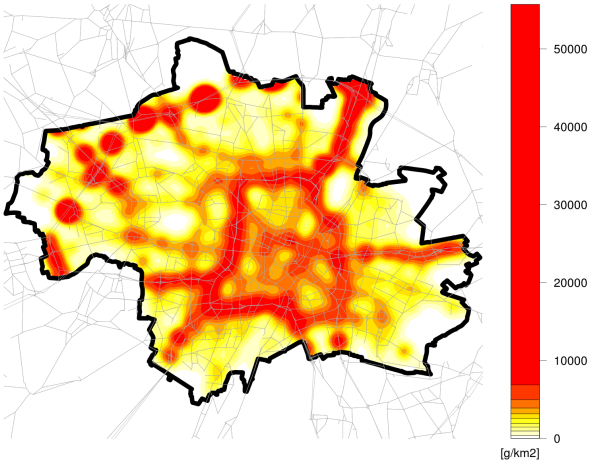
4.4.2 Spatial Analysis of Changes in Car Travel Demand and Air Pollutant Emissions

This section analyzes car travel demand and NO_2 emissions on a spatially disaggregated level. Using the features of the Emission Modeling Tool, demand and NO_2 emissions are in the following aggregated per road segment for a whole day. For visual presentation of the spatial effect within the urban area of Munich, car travel demand (in vkm) and emissions (in g) are spatially smoothed using a Gaussian distance weighting function with a radius of 500 m.[8] Starting with the base case shown in Fig. 4.4, one notices a high level travel demand for the inner ring road, the middle ring road, the main arterial motorways, and the tangential motorway in the north-west of Munich (see Fig. 4.4(a)). As expected, travel demand is

[8] For the functional form of the weighting function of this spatial averaging technique, please refer to Appendix A.2.

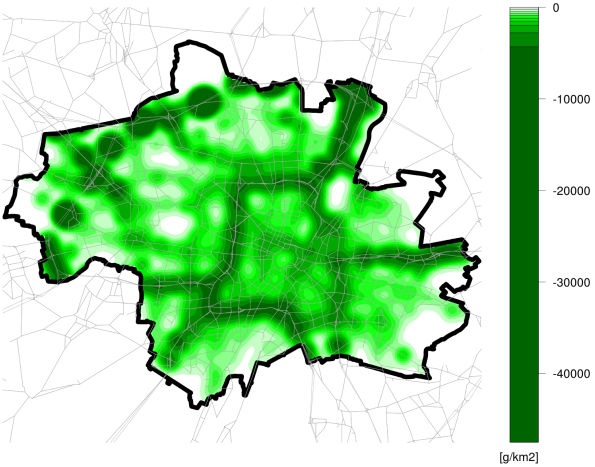


(a) Vehicle kilometers traveled

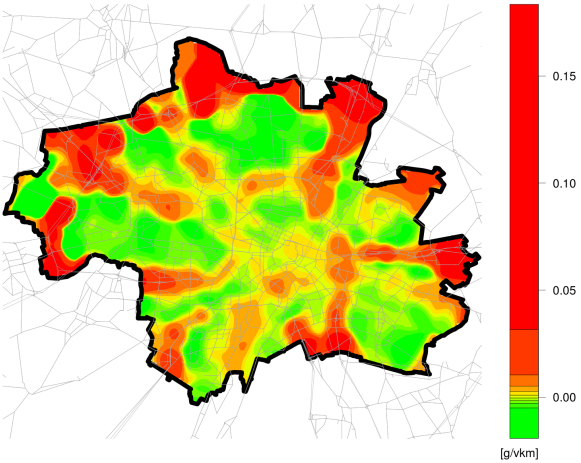


(b) NO_2 emissions

Figure 4.4: Base case: areas with high car travel demand and areas with high NO_2 emissions. Plots based on spatial averaging for all road segments. Values scaled to a 100% scenario.



(a) Absolute change in NO_2 emissions



(b) Absolute change in NO_2 emissions per vehicle kilometer

Figure 4.5: Absolute changes in NO_2 emissions between the base case and policy case 4 (100% price increase). Plots based on spatial averaging for all road segments. Values scaled to a 100% scenario.

highly correlated with the level of exhaust emissions (see Fig. 4.4(b)).[9] The population exposure of NO_2 emissions near these road sections is critical which is also found in the air pollutant concentration levels at monitoring stations, e.g. at Landshuter Allee which represents the western part of the middle ring road (LFU, 2011).

Fig. 4.5 shows the absolute change in NO_2 emissions between the base case and the 100% price increase (policy case 4). As already presented in Sec. 4.4.1, the increase in car user costs leads to an important reduction in emission levels. This finding is now confirmed by Fig. 4.5(a) which decomposes the overall effect in a spatial distribution. The lesson learned when comparing that picture to Fig. 4.4 is that roads with the highest potential for emission reductions are located along the corridors with the highest travel demand (and therefore the highest emissions). Fig. 4.5(a) also shows that potential gains are considerably larger at the medium and high speed roads than, for example, in the inner urban area. The approach allows to show such effects on a detailed single-street level while still being applicable to large-scale scenarios. This allows for both, the identification of relevant corridors (*hotspots*) and the spatially disaggregated analysis of the consequences of policy measures.

In order to answer the question whether spatial patterns of higher emission elasticities compared to demand elasticities can be observed, Fig. 4.5(b) is analyzed. Similar to Fig. 4.5(a), it depicts the absolute difference in emission levels between the base case and the 100% price increase (policy case 4), but now the absolute change in *emissions per vehicle kilometer traveled*. Values above zero imply that vehicles produce more emissions per *km* traveled, whereas values below zero indicate that vehicles emit less emissions for the same distance.

Again, two effects can be observed:

1. *Efficiency decrease*: Average emissions per vehicle kilometer increase on the main arterials and the tangential motorway in the north-west of Munich (red areas).

2. *Efficiency increase*: Average emissions per vehicle kilometer decrease on most of the urban roads (green areas).

[9] The spatial averaging method currently localizes all emissions on a road segment at the center coordinate. This explains why the tangential motorway in the north-west of Munich is shown as a sequence of filled circles rather than an uninterrupted line.

The first effect can be interpreted as follows: in the base case, average speeds on motorways were closer to the (emission) optimal speed of 60 km/h because of more car travel demand than in the policy case. Fewer vehicles on these roads lead to higher emissions per vehicle kilometer, since travelers drive faster. That is, congestion relief leads to higher emissions per vehicle kilometer. This effect somewhat counteracts the biased mode switch effect from above, but is dominated by the latter. A similar finding was obtained by Newman and Kenworthy (1989), who state that the average traffic speed is correlated positively, and not negatively, with gasoline consumption per capita.

The second effect might be interpreted as follows when combining the aggregated and the disaggregated observations: it is likely that due to the reduction in demand, average travel speeds in the corresponding areas get closer to the (emission) optimal speed of 60 km/h. Emissions along a congested *urban* road are about twice as high as when traffic is flowing. When car travel demand is reduced and, thereby, the traffic situation on the road segment changes from stop&go to saturated or even heavy, emissions are more reduced than the flow on that road segment. That is, congestion relief leads to lower emissions per vehicle kilometer especially in urban contexts.

4.5 Summary

In this chapter, a real-world scenario of the Munich metropolitan area was set up and travel demand of a 10% sample (around 200'000 individuals) was simulated with a large-scale multi-agent simulation. The simulation was coupled with detailed emission factors from HBEFA, considering the kinematic characteristics derived from the simulation and highly differentiated vehicle attributes obtained from survey data. Since the simulation keeps track of the approximate position and attributes of every traveler's vehicle during every time step, it was possible to map the kinematic characteristics to the HBEFA traffic situations free flow and stop&go. Thereby, emissions were calculated every time a traveler leaves a road segment, or starts her engine. The mapping of demand (in vkm) or emissions (in g) back to the road segments was therefore rather straightforward.

Subsequently, four policy cases were introduced, where user costs for car were rising from 10 ct/km in four steps up to 20 ct/km. Aggregated price elasticities of demand were found to be in a reasonable range for all

subpopulations. Commuters reacted more sensitively to the price increase than inner-urban travelers, e.g. by changing from car to public transport. Price elasticities of NO_2 emissions turned out to be greater than those of demand. Two possible explanations were given: first, it might happen that an over-proportional fraction of travelers who performed long car trips with high speed levels changed from car to public transport. This was called the *biased mode switch effect*. Second, it seems that travelers are driving faster on formerly congested roads, referred to as the *congestion relief effect*.

A spatially more disaggregated analysis allowed to identify so called *hotspots* that bear high potentials for emission reduction: absolute emissions dropped most in many, but not all, areas where travel demand was high. Furthermore, the spatial analysis showed that the decrease in car travel demand *de*creases the efficiency in terms of emissions per vehicle kilometers on main arterials and tangential motorways. That is, due to higher speeds, fewer vehicles—in this case—lead to higher emissions per vehicle kilometer. However, the analysis also showed that the decrease in car travel demand *in*creases the efficiency in terms of emissions per vehicle kilometer on urban roads. That is, due to higher speeds, fewer vehicles—in this case—lead to lower emissions per vehicle kilometer. Both effects are caused by *congestion relief*. This highlights the fact that the congestion relief can either increase or decrease specific emissions, depending on whether the initial speed on the road segment was higher or lower than the emission optimal speed of 60 km/h.

To summarize, the approach developed in this chapter proved the technical feasibility of introducing heterogeneous user attributes—namely vehicle attributes—into an agent-based transport simulation. It is a first step towards the agent-based internalization of negative environmental effects, which will be addressed in the next chapter. Potentially, the approach can add valuable information to the transport planning and policy decision making process by providing insights into a new emission calculation model for large-scale scenarios. In future studies, it is planned to account for more choice dimensions than just route and mode choice. This is likely to influence the results. Also, the robustness of the results needs to be tested by performing sensitivity analysis. A possible extension would be the modeling of air pollutant concentration which could be used to validate simulation results with measured concentration values.

Chapter 5

Heterogeneity in External Cost Pricing

5.1 Introduction

External costs in the transport sector are known to lead to inefficiencies and social welfare losses. This is due to the fact that people base their decisions on Marginal Private Costs (MPC) and not on Marginal Social Costs (MSC), which is a result of market failures. That is, there exists no market mechanism to account for the costs beyond MPC. The idea of how to internalize the difference between MSC and MPC by a toll has been studied widely in the transportation economic literature (see, e.g., Arnott et al., 1993; Friesz et al., 2004; Vickrey, 1969). The most important dimensions of external costs are usually found to be congestion, air pollution, accidents, and noise. However, optimal toll levels are difficult to compute since they depend on various factors: in principle, a calculation needs to be done (i) for every street in the network, (ii) for every time step, and, when assuming heterogeneous travelers, additionally (iii) for every traveler that is defined by her characteristics such as individual Value of Travel Time Savings (VTTS) or specific vehicle attributes. Additionally, linkages to other sectors of the economy need to be accounted for (de Palma and Lindsey, 2004). For these reasons, so-called second-best pricing has been advanced (Verhoef, 2001).

The computation of second-best tolls has been addressed in several studies (Markose et al., 2007; van den Berg and Verhoef, 2011; Verhoef, 2002). However, most studies focus on congestion pricing (for exceptions see,

e.g., Mitchell et al., 2002; Namdeo and Mitchell, 2008). This is consistent with current estimates that congestion causes the largest part of the external effects (see Maibach et al. (2008), p.103). There is, however, some perception that non-congestion external effects need to be addressed as well (Creutzig and He, 2009); those become especially important for freight traffic (Maibach et al., 2008). In this context, it is important to consider regulatory measures that are not based on charging. These might be dis-satisfactory from an economic perspective, since they always forgo some of the benefits that one can obtain with a well-designed pricing scheme. Yet, they have the advantage of better public acceptance in some countries, see, e.g., the 'low-emission zones' in German cities. Thus, it is useful to investigate economic benefits of regulatory measures, and how close these benefits come to an optimal first-best toll (Proost and van Dender, 2001).

The present chapter presents an approach to (i) internalize emissions costs, and to (ii) consider regulatory measures in comparison. Since congestion was treated in a previous contribution by Nagel et al. (2008), this chapter now focuses on air pollution. The eventual goal will be a comprehensive system which treats all external costs simultaneously. First, an approach is presented that links dynamic traffic flows of the Multi-Agent Transport Simulation (MATSim) to detailed air pollution emission factors provided by the Handbook Emission Factors for Road Transport (INFRAS, 2010). Emissions are computed every time a traveler leaves a road segment. They depend on the traffic state on that segment at the specific time, as well as on the traveler's vehicle attributes. Second, external air pollution emission costs are calculated for Sulfur Dioxide (SO_2), Particular Matter (PM), Nitrogen Oxides (NO_x), Non-Methane Hydrocarbons ($NMHC$), Carbon Dioxide (CO_2), following external emission cost factors provided by Maibach et al. (2008). In a third step, travelers are directly charged with the resulting costs when leaving a road segment. In an iterative process, travelers learn how to adapt their route and mode choice behavior in the presence of this simulated first-best[1] air pollution toll. Information about individual generalized costs for possible routes is provided to every traveler based on information from the previous iteration. The system's state with full air

[1] The simulated toll is first-best with respect to emission cost factors provided by Maibach et al. (2008). For a discussion with respect to which dimensions this calculated toll is nonetheless in line with marginal social cost pricing, please refer to Sec. 5.5.1. In the same section, the reader will also find a discussion on necessary steps towards the calculation of a first-best air pollution toll with respect to all relevant dimensions.

pollution cost pricing is then used as a benchmark for evaluating the effects of a regulatory measure—a speed limitation to 30 km/h in the inner city of Munich, Germany.

The content of this chapter is an edited version of Kickhöfer and Nagel (2013). In addition to the results presented in that paper, this chapter provides visualizations of the spatial distribution of travel demand, emissions levels, and user benefits in Sec. 5.4.1.2 and Sec. 5.4.2.2, respectively. The chapter forms the basis for answering Research Questions 5 and 6. The remainder of this chapter is organized as follows: Sec. 5.2 describes the agent-based microsimulation framework to solve the internalization problem, including an overview of the Emission Modeling Tool and the internalization procedure. Sec. 5.3 introduces the scenario, along with the two policy measures and all relevant assumptions. In Sec. 5.4, the impacts of the two policies on emissions and social welfare are presented. Sec. 5.5 compares the obtained average cost factors per vehicle kilometer to values in the literature, and discusses implications for the interpretation of results. Finally, Sec. 5.6 summarizes the main findings and contributions of this chapter, and provides venues for further research.

5.2 Methodology

This section is composed of three parts: (i) a brief overview of the general simulation approach of MATSim is provided along with the model specifications relevant for this chapter; (ii) the Emission Modeling Tool is shortly described; (iii) it is explained how the emission cost internalization procedure developed in this chapter is embedded in the MATSim framework.

5.2.1 Transport Simulation with MATSim

5.2.1.1 Overview

In the following, only general ideas about the transport simulation with MATSim are presented. For in-depth information about the simulation framework, please refer to Raney and Nagel (2006), or to Sec. 2.2.1, respectively.

In MATSim, each traveler of the real system is modeled as an individual agent. The modeling approach consists of an iterative loop which is composed of the following steps:

1. *Generating Plans*: All agents independently generate daily plans that encode among other things their desired activities during a typical working day as well as the transport mode for every intervening trip. One of these plans is marked as 'selected'.

2. *Simulating Mobility*: All selected plans are simultaneously executed in the simulation of the physical system.

3. *Evaluating Plans*: All executed plans are evaluated by a utility function which typically encodes the attributes travel time and monetary cost, as well as the perception of these attributes. The attributes typically vary within the available choice dimensions (route, mode, time, etc.).

4. *Learning*: Some agents obtain new plans for the next iteration by modifying copies of existing plans. This modification is done by several modules, one for every available choice dimension. The choice between plans is performed with respect to a Multinomial Logit (MNL) model where the total utility of all plans in the choice set enters.

The steps 'Generating Plans', 'Evaluating Plans', and 'Learning' represent the mental layer of the model which is needed for behavioral modeling. 'Simulating Mobility' exhibits the physical layer of the model which is needed to capture interaction between agents in a (capacity) constraint environment. The repetition of the iteration cycle coupled with the agent database enables the agents to improve their plans over many iterations. This is why it is also called learning mechanism. The iteration cycle continues until the system has reached a stable outcome.

5.2.1.2 Model Specifications

Choice Dimensions For the mental layer within MATSim which describes the behavioral learning of agents, a utility based approach is used in this chapter. When choosing between different options with respect to a MNL model (see Sec. 2.2.1.4), agents are allowed to adjust their behavior among two choice dimensions: route choice and mode choice[2]. The former allows individuals to adapt their routes on the road network when going by car. The latter makes it possible to change the transport mode for a sub-tour

[2] In this chapter, car ownership is modeled on a household basis. However, there is no vehicle assignment module which takes into account intra-household decision making. Thus, it might happen that the same car is assigned to two or more agents of the same household at the same time.

Table 5.1: Estimated and adjusted utility parameters; resulting VTTS.

(a) Tirachini et al. (2014)

$\hat{\beta}_{tr,car}$	-0.96	$[\frac{utils}{h}]$
$\hat{\beta}_{tr,pt}$	-1.14	$[\frac{utils}{h}]$
$\hat{\beta}_{c}$	-0.062	$[\frac{utils}{AUD}]$
$\hat{\beta}_{perf}$	N/A	$[\frac{utils}{h}]$
$VTTS_{car}$	$+15.48$	$[\frac{AUD}{h}]$
$VTTS_{pt}$	$+18.39$	$[\frac{AUD}{h}]$

(b) MATSim

$\beta_{tr,car}$	-0.00	$[\frac{utils}{h}]$
$\beta_{tr,pt}$	-0.18	$[\frac{utils}{h}]$
β_{c}	-0.07949	$[\frac{utils}{EUR}]$
β_{perf}	$+0.96$	$[\frac{utils}{h}]$
$VTTS_{car}$	$+12.08$	$[\frac{EUR}{h}]$
$VTTS_{pt}$	$+14.34$	$[\frac{EUR}{h}]$

within the agent's daily plan. Only a switch from car to public transit or the other way around is possible. Trips that are initially done by any other mode remain fixed within the learning cycle. From a research point of view, this approach can be seen as defining a system where public transit is a placeholder for all substitutes of the car mode.

Behavioral Parameters The utility functions used in this chapter are identical to those described in Sec. 2.2.1.3. Following Eq. 2.1, there is a positive utility earned by performing activities which is described by a logarithmic form in Eq. 2.2. Additionally, the travel related part (see Eq. 2.3) considers travel times and monetary costs as attributes of every car and public transit trip. No late penalty applies since this chapter investigates a real-world scenario. Because of a lack of behavioral parameters for the municipality of Munich, estimated parameters[3] are taken from an Australian study by Tirachini et al. (2014); these parameters are shown in Tab. 5.1(a), together with the corresponding VTTS. Necessary adjustments of the parameters are performed in order to meet the MATSim framework. The resulting parameters and VTTS are depicted in Tab. 5.1(b). These adjustments are described in more detail in Ch. 3 where own estimates are used as behavioral parameters. The argument behind the adjustment essentially is that the estimated time related parameters $\hat{\beta}_{tr,car}$ and $\hat{\beta}_{tr,pt}$ consist of the uniform opportunity cost of time $-\beta_{perf}$ (see Sec. 2.2.1.3, and an additional mode specific disutility for traveling $\beta_{tr,car}$ and $\beta_{tr,pt}$, respectively. Since MATSim needs an explicit value for the opportunity costs of time (see Eq. 2.2), it is assumed that traveling with car is not perceived more negatively than waiting. This interpretation is done that way since it

[3] Estimated parameters are in this chapter flagged by a hat.

does not change the VTTS, as a comparison of Tab. 5.1(a) and Tab. 5.1(b) shows: the VTTS are only rescaled from *AUD* to *EUR*.[4] In contrast to Tirachini et al. (2014), the present model does not include access, egress, and waiting times for public transit. Therefore, the Alternative Specific Constant (ASC) β_0 is re-calibrated by a parametric calibration process that aims at holding the modal split distribution over distance as close as possible to the initial distribution. The best fit is found for $\beta_0 = -0.75$.[5] Because of the argument regarding the opportunity cost of foregone activity time when arriving early (see Sec. 2.2.1.3), the *effective* marginal disutility of early arrival is $\beta_{early_{eff}} = -\beta_{perf} \cdot t_{*,i}/t_{perf,i} \approx -\beta_{perf} = -0.96/h$ which is equal to the *effective* marginal disutility of traveling with car $\beta_{tr,car_{eff}}$. The *effective* marginal disutility of traveling by Public Transport (PT) is, by the same argument, $\beta_{tr,pt_{eff}} = -\beta_{perf} \cdot t_{*,i}/t_{perf,i} + \beta_{tr,pt} \approx -\beta_{perf} + \beta_{tr,pt} \approx -1.14/h$.

5.2.2 Emission Modeling Tool

The Emission Modeling Tool was developed and tested by Hülsmann et al. (2011) and was further improved by Kickhöfer et al. (2013). For detailed information, please refer to Sec. 2.2.2.

The tool links MATSim to the Handbook on Emission Factors for Road Transport (HBEFA) database, and essentially calculates warm and cold-start emissions for private cars and freight vehicles. The former emissions are emitted when the vehicle's engine is already warmed whereas the latter occur during the warm-up phase. In the present model, warm emissions differ with respect to vehicle characteristics, traffic state, and road type. Cold-start emissions differ with respect to vehicle characteristics, accumulated distance, and parking duration.

In a first step, vehicle characteristics are obtained from survey data and typically comprise vehicle type, age, cubic capacity and fuel type. They are then used for very differentiated emission calculations. Where no detailed vehicle information is available, fleet averages for Germany are used. For the calculation of warm emissions, MATSim traffic dynamics are mapped to two HBEFA traffic states: free flow and stop&go. In order to identify road types, information from network data is mapped to HBEFA road

[4] 1 *AUD* = 1 Australian Dollar ≈ 0.78 *EUR*, exchange rate in May 2012.

[5] Instead of this rather simple parametric calibration, one could use more advanced techniques, e.g. a novel approach developed by Flötteröd et al. (2011); those authors use their own calibration system 'Cadyts' in order to manipulate the ASC of every link on a route of every traveler's plan in such way that the simulation better reproduces real-world traffic counts.

Table 5.2: Emission cost factors by emission type. Source: Maibach et al. (2008).

Emission type	Cost factor [EUR/ton]
CO_2	70
$NMHC$	1'700
NO_x	9'600
PM	384'500
SO_2	11'000

types, such as motorway, trunk road, distributor road, or tertiary road. For the calculation of cold-start emissions, parking duration and accumulated distance monitored in the simulation. The handbook then provides emission factors for all relevant pollutants differentiated among the characteristics presented above.

In a second step, so-called 'emission events' are generated based on these warm and cold emission factors. The events provide information about person, time, link, and absolute emitted values by emission type. The definition of emission events follows the MATSim framework that uses events for storing disaggregated information as objects in JAVA programming language and as XML in output files. Emission event objects can be accessed during the simulation or generated later on in a post-processing of the standard MATSim events.

5.2.3 Emission Cost Calculation: Internalization

The obtained person and link specific time-dependent emissions now need to be converted into monetary units for the calculation of a first-best toll in order to simulate the full emission cost Internalization policy. For this purpose, emission cost factors differentiated by emission type from Maibach et al. (2008) are used (see Tab. 5.2). Clearly, these cost factors are average costs, collected from different studies. They differ in terms of more local or more global impacts. To name the two most extreme: CO_2 only has an impact on global warming, no matter where it is emitted. In contrast, PM essentially only has local impacts on human health. Therefore Maibach et al. (2008) distinguish between three cost factors for PM: in 'outside build-up areas' the factor is calculated to 75'000 EUR/ton, in 'urban areas' to 124'000 EUR/ton, in 'urban/metropolitan areas' to 384'500 EUR/ton. External costs from CO_2 could easily be internalized by a distance based

toll (e.g. fuel tax), whereas a distance based toll for *PM* would either imply too low tolls in urban areas, or too high tolls in non-urban areas. For the present setup, this means that the emission costs outside of Munich are likely to be overestimated. In consequence, the simulated toll presented in this chapter is first-best with respect to the emission cost factors displayed in Tab. 5.2. Even though it is based on average cost factors, the toll is in line with marginal cost pricing in terms of time-dependent congestion and individual vehicle attributes. For a more detailed discussion, please see Sec. 5.5.1. The following two paragraphs will provide an overview of the first-best emission toll implementation developed by the authors, which is based on the available person- and link-specific, time-dependent emission costs.

Evaluating Plans The core of the emission cost internalization is the *emission cost module* which converts any mapping of emission type to a value into monetary terms. This cost module is generated once the simulation starts. Every time the simulation produces an emission event, the cost module is asked for the monetary value and triggers an 'agent money event' which contains information about person, link, time, and the toll to be paid. One could imagine that, in the simulation, there is a toll gate at the end of each link where travelers directly pay the monetary equivalent of the emissions they produced on that link. When the person's daily plan is evaluated with a (possibly agent-specific) utility function at the end of every iteration, all money events of an agent are considered in the utility calculation. This is a standard MATSim feature which has already been used in other contributions (Kickhöfer et al., 2010; Nagel et al., 2008).

Route Choice Module For the route choice module, the implementation is not as straightforward. Currently, the module is implemented as a best path algorithm, which uses time-of-day-dependent link generalized costs (or disutility of traveling) of the previous iteration (see Sec. 2.2.1.4). At the beginning of every iteration, the module proposes new routes to a certain share of agents based on the attributes travel time and monetary distance costs from the previous iteration. Since travel times and distance costs are equal for all agents, the module only needs to generate new routes based on global information. Now, with the internalization of emission costs, the disutility of traveling on every link is additionally dependent on the agent's vehicle characteristics. Therefore, the module is modified

to generate new routes on very disaggregated information by calculating person-specific expected emission costs in every time interval. Even though the implementation is working properly, it makes the simulation relatively slow, for a 10% sample of the scenario in Sec. 5.3.1, by a factor of 7. Therefore, a 1% sample is used in the present chapter.[6]

5.3 Case Study V: High-resolution Air Pollution Tolls—Munich, Germany

In this section, a short introduction is given into the large-scale real-world scenario of the Munich metropolitan area. This is followed by a definition of the available choice dimensions as well as the utility functions. Finally, two policy measures are defined: First, the *Zone 30 policy* is a regulatory measure of limiting the maximum speed in the inner city of Munich to 30 km/h. Second, the *Internalization policy* uses the methodology from Sec. 5.2.3 in order to charge every car user when leaving a link dependent on her individual emissions.

5.3.1 Scenario Setup

The initial scenario setup for this case study is identical to the one presented in Sec. 4.3.1. Therefore, only key figures are presented here.

The road network consists of 17'888 nodes and 41'942 road segments. It covers the federal state of Bavaria, being more detailed in and around the city of Munich and less detailed further away. Every link is characterized by maximum speed, flow capacity, and number of lanes. This information is stored in the road type which is for the emission calculation mapped to a corresponding HBEFA road type.

In order to obtain a realistic time-dependent travel demand, several data sources have been converted into the MATSim population format. The level of detail of the resulting individual daily plans naturally depends on the information available from either disaggregated Stated Preference (SP)

[6] In order to run the simulation with a sample of 1%, all flow capacities are scaled down to 1%. This means, for example, that a link with a capacity of 3600/h will now allow one vehicle every 100 seconds. Clearly, this leads to larger fluctuations; for example, one vehicle changing routes has a much larger impact. In order to dampen some of these fluctuations, the link storage capacities, which produce spillback, were reduced to 3% instead of 1%. Other studies for car traffic indicate that this approach is sufficient to obtain realistic congestion patterns (see, e.g., Nagel, 2008, 2011). Since congestion patterns are plausible, it is assumed that the emissions are realistic as well.

data or aggregated population statistics. Therefore, *three subpopulations* are created, each corresponding to one of the three different data sources:

- Urban population (based on Follmer et al. (2004)):
  The synthetic population of Munich is created on the base of very detailed survey data provided by the municipality of Munich RSB (2005), named Mobility in Germany (MiD 2002). Whole activity chains are taken from the survey data for this population. MiD 2002 also provides detailed vehicle information for every household. Linking this data with individuals makes it possible to assign a vehicle to a person's car trip and thus, calculating emissions based on this detailed information. As of now, there is however no vehicle assignment module which models intra-household decision making. It is, therefore, possible that a vehicle is assigned to more than one person at the same time. The synthetic urban population of Munich consists of 1'424'520 individuals.

- Commuter population (based on Böhme and Eigenmüller (2006)):
  Unfortunately, the detailed data for the municipality of Munich does neither contain information about commuters living outside of Munich and working in Munich nor about people living in Munich and working outside of Munich. The data analyzed by Böhme and Eigenmüller (2006) provides information about workers that are subject to the social insurance contribution with the base year 2004. With this information, a total of 510'150 synthetic commuters are created from which 306'160 people have their place of employment in Munich. All commuters perform a daily plan that only encodes two trips: from their home location to work and back.

- Freight population (based on ITP and BVU (2007)):
  Commercial traffic is based on a study published on behalf of the German Ministry of Transport by ITP and BVU (2007). It provides origin-destination commodity flows throughout Germany differentiated by mode and ten groups of commodities. After converting flows that are relevant for the study area into flows of trucks, this population consists of 158'860 agents with one single commercial traffic trip.

Overall, the synthetic population now consists of 2'093'530 agents. For commuters and freight, no detailed vehicle information is available. Emis-

sions are therefore calculated based on fleet averages for cars and trucks from HBEFA.

5.3.2 Policy Design and Simulation Procedure

Policy Design The policies that will be analyzed in this chapter are the following:

- Base case: unchanged cost structure (see below)
- Policy case 1 (Zone 30): maximum speed on all roads within the middle ring road is limited to 30 km/h (see Fig. 5.1)
- Policy case 2 (Internalization): for car users, additional costs apply for every link; they are dependent on the emissions emitted by an agent (see Sec. 5.2.3)

The reason for choosing a speed limitation policy for evaluation is that, in Germany, it is currently discussed to regulate the maximum speed in the inner cities to 30 km/h. The current speed limits are (with some exceptions) 60 km/h on primary roads, 50 km/h on secondary roads, and 30 km/h on tertiary roads.

User costs[7] for car are always fixed to 30 $EURct/km$. For the Internalization policy, additional costs apply (see above). User costs for public transit are assumed to be constant at 18 $EURct/km$ for the base case and both policy cases.

Simulation Procedure To speed up computations, a 1% sample is used in the subsequent simulations. For choosing between travel alternatives, the re-planning modules RCM and MCMb) from Sec. 2.2.1.4 are used. They allow for route choice and mode choice, respectively. The car traffic flow simulation and the simulation of other modes follow the description in Sec. 2.2.1.2. That is, travel times for PT are approximated by a travel speed of 25 km/h and a distance which is 1.3 times the beeline distance between activity locations. For the base case, the simulation is set up as follows:

- For 800 iterations, 15% of the agents perform route adaptation, 15% change the transport mode for a car or PT sub-tour in their daily plan, and 70% switch between their existing plans according to Eq. 2.5.

[7] Please note that the term 'user costs' is referred to as out-of-pocket costs for the users.

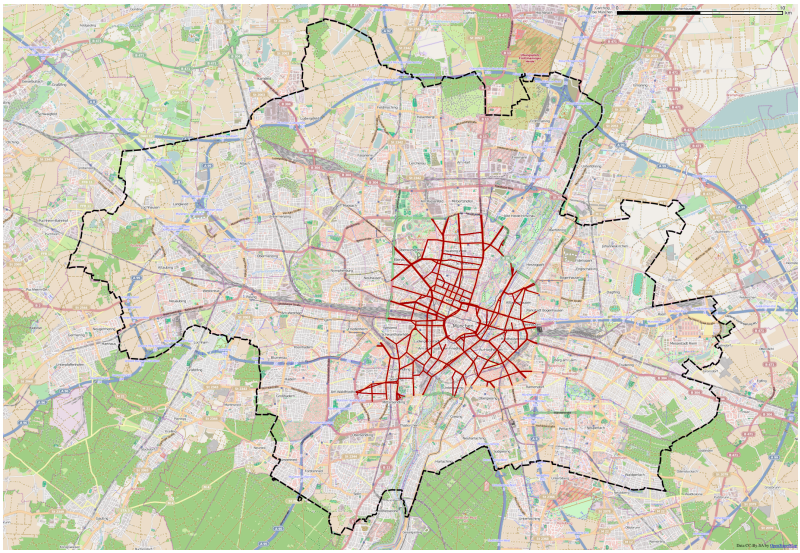


Figure 5.1: Policy design of the Zone 30. Road segments (in red) where the speed limitation applies. Source: author's image using map data from `www.openstreetmap.org` (© OpenStreetMap contributors).

- Between iteration 801 and 1000, route and mode adaptation is switched off; in consequence, agents only switch between existing options according to Eq. 2.5.

The output of iteration 1000 is then used as input for the continuation of the base case and the two different policy cases. All simulations are continued for another 500 iterations. Again, during the first 400 iterations 15% of the agents perform route adaption while another 15% of agents choose between car and public transit for one of their sub-tours. The remaining agents switch between existing plans. For the final 100 iterations only a fixed choice set is available for all agents. When evaluating the impact of the two policy measures, the final iteration 1500 of every policy case is compared to iteration 1500 of the base case. Emissions are calculated for iteration 1500 of all cases. Public transit is in the present chapter assumed to run emission free; it is therefore a placeholder for all environmentally friendly transport modes. PT travelers are teleported between activity locations with a travel speed of 25 km/h. Beeline distances between activity locations are for this

purpose multiplied by a factor of 1.3, capturing detours resulting from PT network geometries (see Sec. 2.2.1.2).

5.4 Results

In this section, different changes to the system are presented that result from the two policy measures. The main goal is to answer the question how close the regulatory measure (Zone 30) comes to an optimal first-best toll (Internalization) in terms of emission reduction and economic benefits. A further discussion of the results is provided in Sec. 5.5. All results in this section are rescaled from the 1% sample to the full scenario for a regular week day in the scenario described in Sec. 5.3.1.

5.4.1 Emissions

5.4.1.1 Emissions by Subpopulation

Starting with analyzing the final iteration of the base case, Fig. 5.2 shows absolute emission levels by emission type and subpopulation. Note that the commuter population is differentiated into people commuting *to* Munich for work (commuters), and people commuting *from* Munich to work outside of Munich (reverse commuters). Also note that the scale is different for different pollutants in order to make absolute values visible in one graph. One can clearly see that the urban population only contributes to a relatively small part for most emission types, even though these people represent 68% of the total population and perform more trips per day than the other subpopulations. Only *NMHC* is relatively more important for the urban population. This is presumably due to the fact that *NMHC* emissions are highest for cold-starts and during the warm-up phase of the vehicle (Schmitz et al., 2000). Thus, two possible explanations come to mind: First, urban car travelers drive relatively short distances (average trip distance: 6.29 km). This means that—in some cases—the engine is not even completely warmed up when reaching the destination. Second, because of a higher number of trips per day, the urban population produces more cold starts per car user during a day than the other subpopulations who—in the present model—only perform two trips (commuters and reverse commuters) or one trip (freight), respectively. Commuters (14.6% of the total population) and reverse commuters (9.8%) seem to have a similar split of the different pollutants. However, commuters emit in total about three times as much as reverse commuters since they drive longer distances

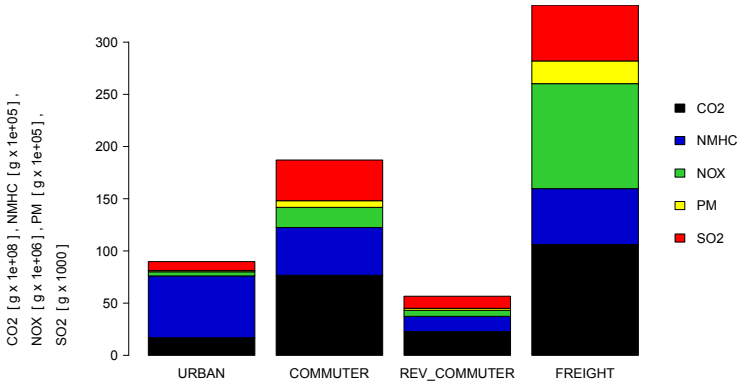
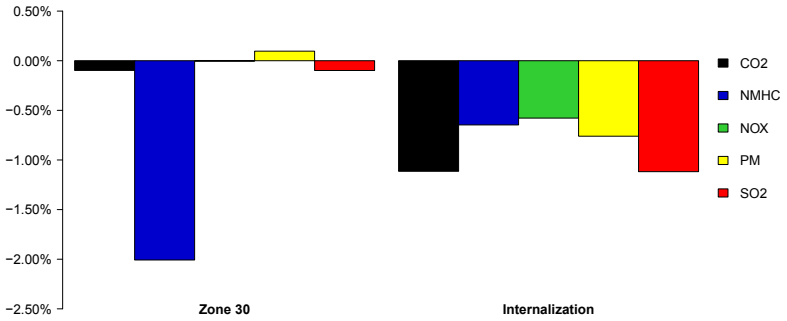


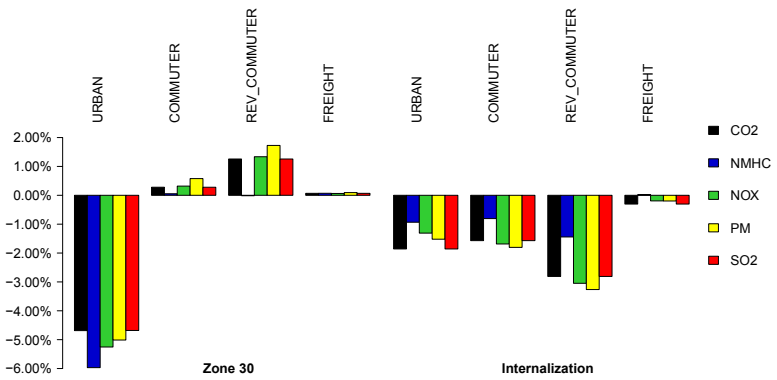
Figure 5.2: Base case: Absolute emission levels by type and subpopulation. Values scaled to a 100% scenario.

(average commuters: 66.56 km; average reverse commuters: 56.26 km). Finally, freight traffic also drives rather long distances (average freight: 111.20 km). Even though freight traffic represents only 7.6% of the total population, it contributes to a major part of total emissions: its share for CO_2 is roughly 50%, for $NMHC$ 30%, for NO_x 78%, for PM 70%, and for SO_2 47%. Here, the distance effect might play a role, but the major reason presumably is that trucks produce much higher emissions per vehicle kilometer than normal cars.

To answer the question on how close the Zone 30 policy comes to the Internalization policy in terms of emission reduction, Fig. 5.3(a) shows the relative changes in emissions for the two policies. The Zone 30 reduces $NMHC$ by around 2%, CO_2 and SO_2 are only slightly reduced by 0.1%, NO_x remains unchanged, and PM is even increasing. The impacts of the Internalization policy result in a much more homogeneous picture: all pollutants are reduced by 0.6% to 1.1%. Fig. 5.3(b) decomposes the information from Fig. 5.3(a) to the different subpopulations. The picture becomes even more interesting: the Zone 30 leads to a strong emission reduction of 5% to 6% for the urban population. All other subpopulations produce *more* emissions. In contrast, the Internalization policy leads to a rather strong decrease of emissions, by 1% to 2% for urban travelers and commuters and between 1.5% and 3% for reverse commuters. Only freight traffic does not significantly reduce emissions.



(a) By emission type



(b) By emission type and subpopulation

Figure 5.3: Policy cases: Relative changes in emissions.

Table 5.3: Changes in modal split and average car distance traveled.

(a) Zone 30

Subpopulation	Δ car trips [%]	Δ avg. car dist. [km]
URBAN	−7.00	−0.08
COMMUTER	−0.43	+0.29
REV_COMMUTER	−0.87	+1.01
FREIGHT	±0.00	+0.02

(b) Internalization

Subpopulation	Δ car trips [%]	Δ avg. car dist. [km]
URBAN	−0.59	−0.10
COMMUTER	−0.62	−0.89
REV_COMMUTER	−1.22	−1.52
FREIGHT	±0.00	−0.15

Given the available choice dimensions presented in Sec. 5.3.2, the above emission effects result directly from re-routing and changes in the modal split. Additionally, they may result indirectly from changes in congestion. Tab. 5.3(a) and Tab. 5.3(b) show the relative change in car trips and the absolute change in average car distance traveled. Expectedly, the car mode becomes less attractive for both policies as the second column in either table shows. The Zone 30 reduces car trips of urban travelers by 7%. The remaining car users on average drive slightly shorter distances (−0.08 km). This may be due to the fact that travelers with longer distances have a tendency to switch to PT; or the remaining car users re-route to shorter paths. A combination of the two effects is most likely. When comparing this to the Internalization policy, it becomes obvious that the Zone 30 pushes more urban travelers to public transit. For commuters and reverse commuters, the change in number of car trips is not very different for the two policies. However, for the Zone 30, the re-route effect for the remaining car users becomes visible by *longer* average distances in order to avoid the unattractive zone with the speed limitation (commuters: +0.29 km, reverse commuters: +1.01 km). Freight traffic also re-routes around the regulated zone.

Overall, one can conclude that in terms of total emission reduction, the Zone 30 is considerably less successful than the Internalization policy. Even

though the Zone 30 reduces the emission levels of the urban population more than the Internalization policy, it increases the emission levels of the other subpopulations; The net effect results in an overall higher emission level.

5.4.1.2 Emissions: Spatial Effects

For visual presentation of the spatial effect within the urban area of Munich, absolute emissions (in g) and specific emissions (in g/vkm) are spatially smoothed using a Gaussian distance weighting function with a radius of 500 m.[8] Spatial effects of Nitrogen Dioxide (NO_2) emissions for the base case are shown in Fig. 5.4. Clearly, one can observe the highest emission levels on primary roads with high traffic volumes.

Absolute changes in NO_2 emissions after introducing the Zone 30 policy are depicted in Fig. 5.5.[9] As Fig. 5.5(a) nicely shows, absolute emissions drop within the regulated zone. However, because of re-route (and possibly congestion) effects, emissions strongly increase especially on the middle ring road and on tangential motorways. Fig. 5.5(b) can be interpreted as a rather striking finding: Even though absolute emissions drop, emissions per vehicle kilometer increase in the regulated zone. That is, the regulatory measure results makes the inner city unattractive and therefore induces modal shift towards PT, as well as re-routing around the zone. However, the remaining cars in the zone drive slower, remain longer in the system, and therefore produce more emissions per vehicle kilometer. In that sense, the possible goal of reducing emissions in the inner city is achieved but some of the gains are directly eliminated by the more polluting remaining cars.

5.4.2 Economic Evaluation

5.4.2.1 User Benefits by Subpopulation

Fig. 5.6(a) shows absolute changes in user benefits by subpopulation for the two policy cases. Changes in user benefits (blue bars) are calculated as income equivalents by multiplying the difference of the logsum term[10]

[8] For the functional form of the weighting function of this spatial averaging technique, please refer to Appendix A.2.

[9] For the corresponding illustrations of the effects of the Internalization policy, see Appendix B.1

[10] For the formulation of the logsum term in units of utility, see Eq. 2.11. For a stable formula on how to calculate the logsum in the MATSim framework, see Eq. A.11. For a discussion on potential issues and the applicability of the logsum approach for measuring individual utility changes, see Sec. 2.3.2.

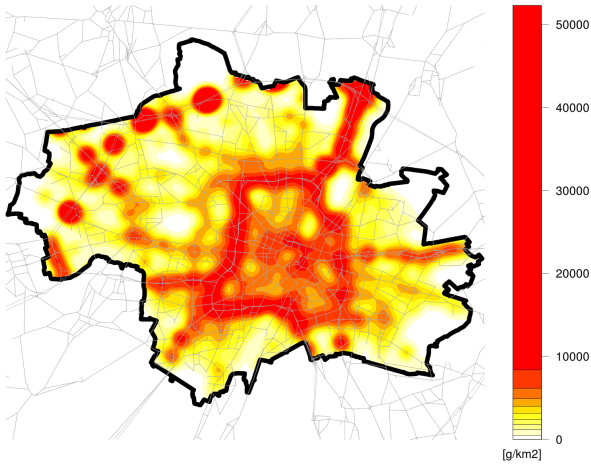
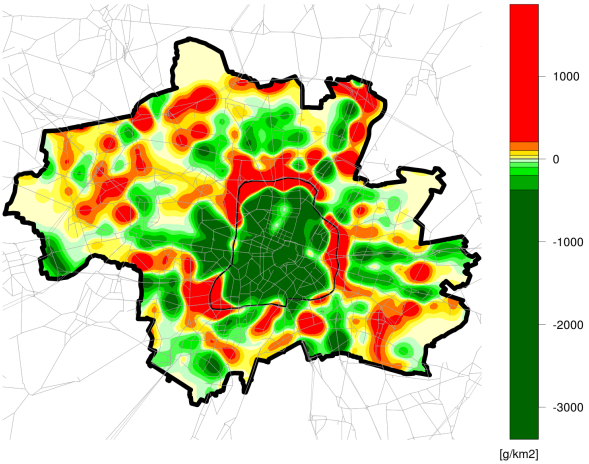


Figure 5.4: Absolute NO_2 emissions for the base case. Plots based on spatial averaging for all road segments. Values scaled to a 100% scenario.

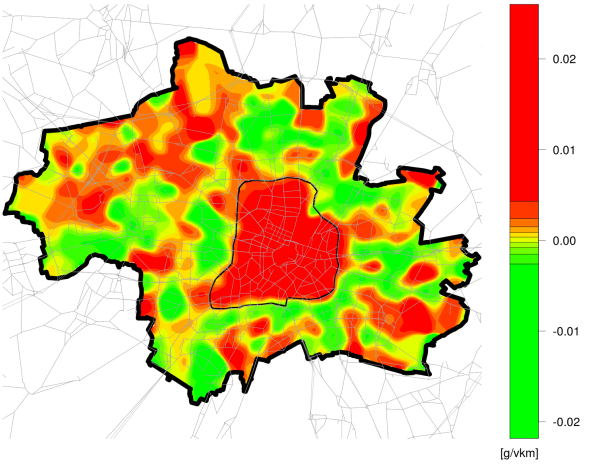
for every member of the respective subpopulation by the inverse marginal utility of money according to Eq. 2.13 and then aggregating the results by applying Eq. 2.14.

The Zone 30 policy leads to a loss in user benefits for all subpopulations, with the effect on urban travelers being the strongest, while almost having no effect on freight traffic. That is, urban travelers react most sensitively by changing from car to public transit, especially for longer trips. The remaining car users can barely profit from reduced car demand in the city since travel times by car are no longer determined by congestion but by the new maximum free speed of 30 km/h. Commuters and reverse commuters change to PT only for shorter trips. The remaining car users drive longer distances (e.g. on the middle ring road) since driving though the inner city has become less attractive because of the speed limit. Freight traffic can only change routes which seems to have a minor effect on user benefit.

The Internalization policy on the right side yields quite different results: commuters, reverse commuters and freight all lose in terms of user benefits; the loss is most pronounced for freight traffic. This intuitively makes sense since freight traffic contributes to a major part of total emissions (see Sec. 5.4.1.1) and therefore it has to pay a major part of the total emission costs. In contrast, the urban population even gains slightly in terms of

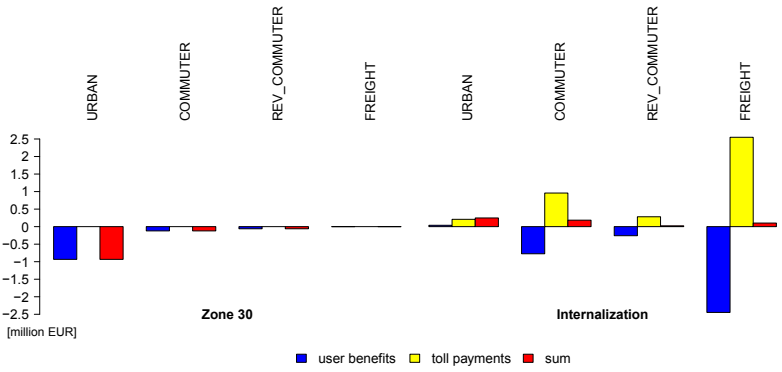


(a) Absolute changes in NO_2 emissions

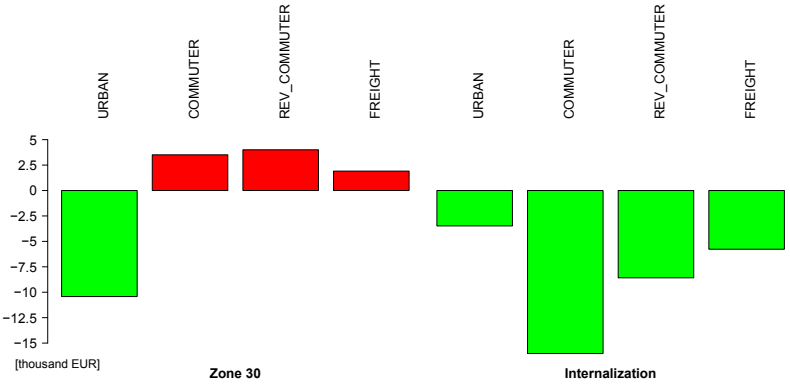


(b) Absolute changes in NO_2 emissions per vehicle kilometer

Figure 5.5: Zone 30: Absolute changes in NO_2 emissions. Plots based on spatial averaging for all road segments. Values scaled to a 100% scenario.



(a) Absolute changes in user benefits, redistributed toll payments, and sum by subpopulation



(b) Absolute change in external emission costs by subpopulation

Figure 5.6: Policy cases: Welfare analysis by subpopulation. Values scaled to a 100% scenario.

user benefits despite the toll they have to pay. Time gains for the urban population slightly overcompensate the negative effect of the toll payments.

When assuming a redistribution of the toll payments of every subpopulation (yellow bars in Fig. 5.6(a)) to the respective subpopulation, one obtains the net welfare effect for that population (red bars). Interestingly, the redistribution of the toll payments overcompensates the loss in user benefits for commuters, reverse commuters, and freight. For urban travelers, the welfare gain becomes even more important, being the highest of all subpopulations. That is, for all subpopulations, the emission toll *implicitly* reduces congestion and in that way also works as a congestion pricing scheme that increases welfare.

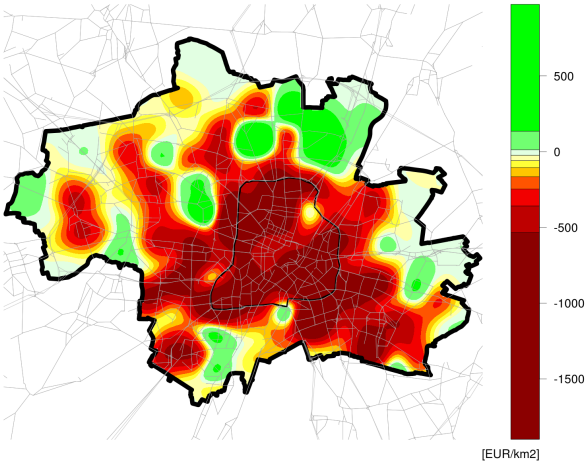
In addition to the changes in user benefit and toll payments, a comprehensive calculation of the total welfare effect needs to include the absolute monetary change in emission costs resulting from the policies. Cost reductions for society because of lower emission levels are—in contrast to time gains—not included in the user benefit calculation; this is due to the fact that emission costs are true external costs for the transport market.[11] Fig. 5.6(b) depicts the absolute change in external emission costs resulting from the two policies. This figure looks naturally quite similar to Fig. 5.3(b), since it the emission values are only converted into monetary terms. The figure allows interesting insights into the welfare effect of the two policies: For the Zone 30, the deadweight loss for commuters, reverse commuters, and freight from Fig. 5.6(a) is becoming even larger because of additional emission costs. The deadweight loss for urban travelers is only reduced by a small amount. For the Internalization policy, all user groups contribute to a reduction in deadweight loss of society. However, when looking at the scaling of the y-axis, it becomes obvious that these changes in emission costs do not have the potential of compensating any losses from Fig. 5.6(a).

5.4.2.2 User Benefits: Spatial Effects

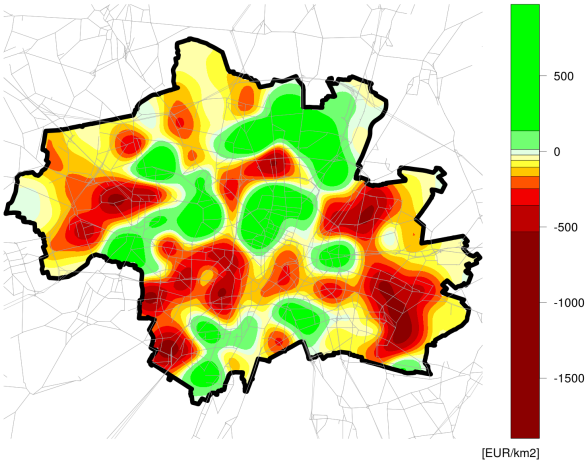
For visual presentation of the spatial effect within the urban area of Munich, absolute and average user benefits are spatially smoothed using a Gaussian distance weighting function with a radius of 1000 m.[12]

[11] The same is true for other external costs that are currently not quantified in the present model, e.g. noise emissions, accidents, etc. It is expected that the emission toll, again, implicitly reduces these external costs and therefore has further positive effects on the wellbeing of individuals or on property values.

[12] For the functional form of the weighting function of this spatial averaging technique, please refer to Appendix A.2.

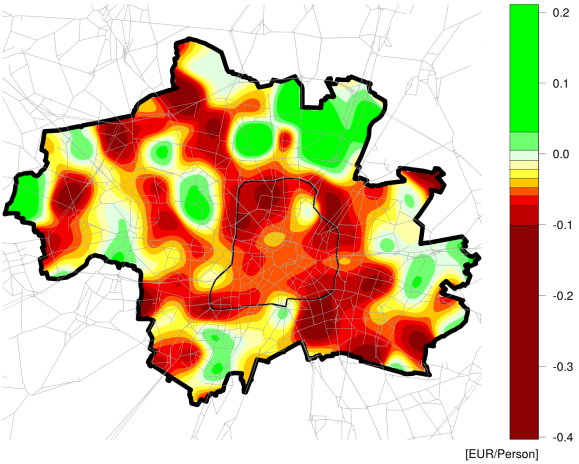


(a) Zone 30

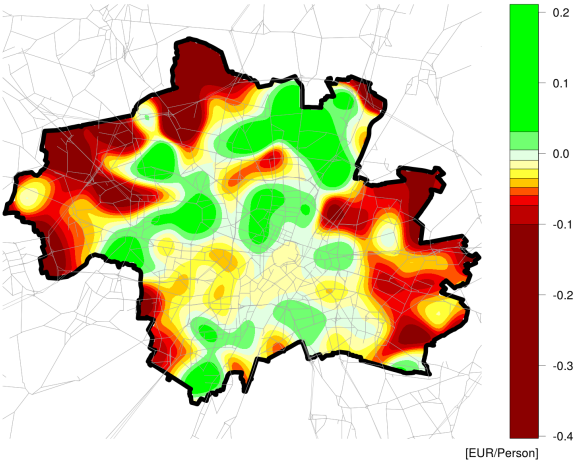


(b) Internalization (excluding a redistribution of toll payments)

Figure 5.7: Changes in absolute user benefits. Plots based on spatial averaging for all home locations. Values scaled to a 100% scenario.



(a) Zone 30



(b) Internalization (excluding a redistribution of toll payments)

Figure 5.8: Changes in average user benefits. Plots based on spatial averaging for all home locations. Values scaled to a 100% scenario.

Fig. 5.7 shows changes in *absolute* user benefits in EUR/km^2 for the two policy cases. These changes are mapped to each person's home location, in order to identify where the most affected areas of the policy measures are located. For the Zone 30 policy in Fig. 5.7(a) one notices rather strong losses for people who live in and around the regulated zone. That is, these people bear most of the losses of the urban travelers from Fig. 5.6(a). Presumably, they are most affected by the speed limitation and by the increase in car travel times resulting from the re-route effect of the zone, which pushes traffic on the middle ring road. Both effects lead to lower accessibility. The same analysis for the Internalization policy is shown in Fig. 5.7(b). Importantly, this figure shows changes in user benefits *excluding* a redistribution of toll payments. Therefore, the Internalization policy looks less advantageous than it is.[13] The impacts in this picture are less coherent than for the Zone 30: gains and losses are distributed throughout the city area. However, one notices an overall higher level of user benefits than with the Zone 30. It also appears that the aggregated losses for the Internalization case occur more in the outer areas of the city, whereas people within the middle ring road mostly gain.

It is, at this point, important to note that the plots in Fig. 5.7 implicitly contain the population density: individual gains or losses in areas with many people appear more pronounced than the same individual gains or losses in less populated areas. In order to correct for this effect, Fig. 5.8 shows changes in *average* user benefits in $EUR/Person$ for the two policy cases. Consequently, for the Zone 30 policy, losses in the outer areas of the city appear more pronounced. They are mostly located along the tangential motorway in the north-west, along main arterials, and along the inner ring road. This might indicate that the re-route effect induced by the regulated zone pushes traffic onto the major roads of the city. An exception is the arterial motorway in the north of the city. For the Internalization policy (again excluding a redistribution of toll payments), the losses in the outer areas of the city also appear more pronounced. That is, people in average lose more the further they live away from the city center. Intuitively, this makes sense, since they tend to drive longer distances and therefore need to pay more air pollution toll, or change to a slower transport mode.

An interesting question rises in this context: which of the graphical representations is more suitable for decision support? Changes in absolute

[13] For a visual representation of the welfare effects of the Internalization policy *including* different redistribution schemes of toll payments, see Appendix B.2.

user benefits or changes in average user benefits. Absolute user benefits seem more appropriate to identify areas with the most important contributions to the overall welfare effect. Since they implicitly contain the population density, they represent the democratic level of compliance or refusal in the respective urban district. For (local) politicians this could be helpful for arguing that their constituency is gaining or losing the respective amount. Average user benefits seem more appropriate for the identification of areas where people *experience* the biggest changes in welfare levels. This might be interesting for analyzing the magnitude of compliance or refusal. For instance, if people in a sparsely populated district massively lose, they might strongly refuse the policy. People in a densely populated district that slightly gain might not even perceive the change in wellbeing.

In summary, it can be said that such analysis is—in contrast to the spatial representation of emissions in Sec. 5.4.1.2—only possible in the framework of an activity-based multi-agent simulation. This approach allows for the mapping of benefits, which user experience over the whole day, back to their home location.

5.5 Discussion

5.5.1 Discussion of the Internalization Approach

Obtained Average Emission Costs Tab. 5.4 shows average external emission costs per vehicle kilometer for the different subpopulations that are calculated from the simulation of the base case.[14] The second column depicts average emission costs per vehicle kilometer including CO_2, the third column excluding CO_2. When comparing the latter to values from the literature, one can state that the approach of coupling MATSim with HBEFA and then using cost factors from Maibach et al. (2008) leads to plausible average emission costs per vehicle kilometer: e.g. Parry and Small (2005) use local pollution cost factors for automobiles of 2.0 $USDct/mile$ or roughly 1.23 $EURct/km$. This estimate is very close to the resulting value for urban travelers in the present scenario. Obviously, freight traffic causes much higher pollution costs since it produces more emissions. The values for commuter and reverse commuter are identical and distinctly lower than

[14] Please note that the numbers in Tab. 5.4 are an output—not an input—of the simulation in order to compare the values to other sources. Remember that the individual toll is highly differentiated since it depends on vehicle attributes and time-dependent dynamic traffic flows of the simulation.

Table 5.4: Base case: resulting average emission cost factors by subpopulation [$EURct/km$].

Subpopulation	incl. CO_2	excl. CO_2
URBAN	2.71	1.20
COMMUTER	2.27	1.02
REV_COMMUTER	2.25	1.02
FREIGHT	14.51	10.29

those for urban travelers. This indicates that the emission tool, since it is accounting for different traffic states, feeds the cost calculation module with spatially and temporally differentiated values: commuters and reverse commuters who drive a major part of their routes on a non-congested network outside of Munich produce less emissions per vehicle kilometer. That is, the high-resolution emission costs in the present model are *based* on average cost factors; these are, however, average costs per amount of pollutant, and since these amounts are influenced by congestion effects and vehicle attributes, the resulting costs are marginal costs with respect to congestion and vehicle attributes.

Nonetheless, in order to calculate marginal air pollution costs also with respect to damage of human health, cost factors would need to differentiate among the number of individuals that are exposed to a certain pollution concentration. The implications of this drawback for the interpretation of results are discussed in the following paragraph.

Implications for the Interpretation of Results Looking again at Fig. 5.6(a) and Fig. 5.6(b) clarifies that the speed limitation to 30 km/h in the inner city of Munich leads to more market inefficiencies than a 'do-nothing' strategy. When taking the Internalization policy as a benchmark, these two figures show that the emission reduction is for urban travelers beyond the economic optimum; for all other subpopulations, this speed limitation even leads to an increase in negative environmental externalities. That is, generalized prices beyond the economic optimum for the urban population, generalized prices below the economic optimum for all other subpopulations.

Yet, one could argue that the Zone 30 yields much better results when looking at *exposure* to emission concentration rather than emissions. Emission cost factors from Maibach et al. (2008) are average costs and, thus, probably too low in the inner city and too high outside of Munich. For

this reason, it is planned to model the whole impact-path-chain of air pollution in the near future which implies an exposure analysis of the whole population, and monetizing the effects on human health. A first step into the modeling of emission concentration has been done by Hülsmann et al. (2013), who introduce pricing measures for emission concentration hotspots. The next steps will be to model the number of people that are exposed to that concentration, and finally, to monetize that effect. Once exposure is considered, one may argue that the optimal toll should be corrected exactly for that effect. I.e., by putting weights on every link that are differentiated by emission type and resulting exposure. Weights for CO_2 would be unchanged since it only has a global effect, whereas weights for PM would be higher in urban areas due to the strong local impact on human health. A different approach could also be worth modeling: the calculation of an optimal toll *given* the desired emission reduction in the area under consideration. This may, similar to the Zone 30, be dis-satisfactory from an economic perspective but may arguably be more likely to happen in reality than the implementation of a first-best pricing scheme.

5.5.2 Discussion of Freight Traffic

Truck Types As mentioned earlier, freight traffic contributes to a major part of total emissions while only representing under 10% of the total population. This is the result of two effects: (i) freight drives longer average distances than all other subpopulations. (ii) freight produces more emissions per vehicle kilometer. Additionally to these two effects, it is likely that bigger trucks drive longer distances than small trucks. Since in the present chapter, all trucks are assumed to be of the same vehicle type, the contribution to total emissions is, in reality, expected to be even higher than presented in Sec. 5.4.1.1.

Behavioral Parameters The behavioral modeling of freight was not the focus of the present chapter. As mentioned in Sec. 5.3.1, freight demand was included into the scenario in a simplified way for completeness. Since no behavioral parameters for freight were available, they are the same as for all other agents. In consequence, the assumed VTTS is lower than usually found in empirical studies. This implies that the reaction of freight to the different policy cases is too sensitive. In consequence, the results for freight are biased. However, since freight is only allowed to adapt routes and not

mode as all other subpopulations, this bias is unlikely to be very important. In order to get an estimate of the resulting effect, the impact of this bias on travel patterns and economic evaluation of the policy cases is discussed next:

- General: A higher VTTS for freight implies (ceteris paribus) a lower marginal utility of money. Given the computed behavioral reactions, this results in larger absolute welfare changes than presented in this chapter when monetizing utility gains.

- Zone 30: A too low VTTS has no effect on routing since there is no trade-off between a toll and travel time. Only the general effect from above applies in the economic evaluation. The welfare effects for freight are very small (see Fig. 5.6(a)), and even multiplying them by a factor would not change the results significantly.

- Internalization: A too low VTTS has an effect on routing: it results in routes with too short distances and too long travel times. A higher VTTS would therefore result in (i) longer distances and (ii) shorter travel times. With longer distances, if the distance effect of emissions dominates the congestion effect, freight would produce even higher emissions and also pay more toll than presented in this chapter. With shorter travel times, freight would have higher utility gains because of congestion relief. Additionally, the above monetization effect applies in the economic evaluation. That is, for the internalization policy, the results presented in this chapter underestimate the toll payments of freight, as well as the welfare change after redistribution.

The above clearly shows that there is a strong need for improving demand and behavioral modeling of freight transport. Especially because of its major impact on total emissions, a more profound understanding of the relevant processes in freight transport is necessary in order to be able build policy-sensitive demand on a micro-level.

5.5.3 Discussion of Long-Term Changes to the Vehicle Fleet

The results presented in Sec. 5.4 provide short-term emission and welfare effects with respect to the choice dimensions route choice and mode choice. On a very different level of detail, this section now aims at presenting rough estimates on how big the short-term impact is in comparison to

possible long-term user reactions. These long-term reactions might, for instance, include changes in the vehicle fleet[15]: the environmental toll could induce people to buy more fuel/emission efficient cars. Two possible long-term reactions come to mind: First, some users that—in the short run—changed to public transit would in the long run possibly buy a more emission efficient car and change back to car. Second, users who travel by car before and after the policy could also buy more emission efficient cars. Compared to the short-term impacts of the Internalization policy, the former would increase car vehicle kilometers traveled as well as emissions, and therefore also increase toll payments. The latter is likely to increase vehicle kilometers traveled because traveling with car becomes cheaper, but it would lower emissions per vehicle kilometer; the impact on total toll payments is dependent on the magnitude of these sub-effects. Parry and Small (2005) state that "[...] less than half of the long-run price responsiveness of gasoline consumption is due to changes in VMT" (Vehicle Miles Traveled). According to them, the rest of the decrease in gasoline consumption results from changes in the vehicle fleet. Assuming a linear relationship between gasoline consumption and emissions, this would imply that vehicle kilometers in the long run and for the same price signal would drop by less than 0.5 of the reduction in emissions. Erath and Axhausen (2010) calculate propensities to change car types from a discrete-continuous choice model for an average fuel price increase of 100%. In principle, it would be possible to transfer the resulting propensities to the MATSim framework. Since there is, however, not a similar study for the city of Munich, randomly drawing agents in the population for vehicle replacement would result in biased statistics. The reason for this is that the probabilities would not be linked to the users' preferences, socio-demographics, or locations.[16]

In order to determine the long-term effect of changes in the vehicle fleet for the current setup, parametric studies were performed with the assumption that all vehicles are affected uniformly by the improvement

[15] Additionally there might be changes in activity location choice, changes in the frequency of performing activities, and changes in bundling activities. A possible approach on how to deal with these possible user reactions within the MATSim framework can be found in Horni et al. (2012).

[16] Consider the following example with two persons owning a car of the same vehicle class: Assume that the probability of buying a more emission efficient car as reaction to the Internalization policy is 50% for their vehicle class. When randomly drawing, one would expect one of the persons to buy a new car. However, if the first person lives next to a public transit line and the second is not, it is more likely that the second person buys a more fuel efficient vehicle; the first could more easily change to public transport and might not buy a new car.

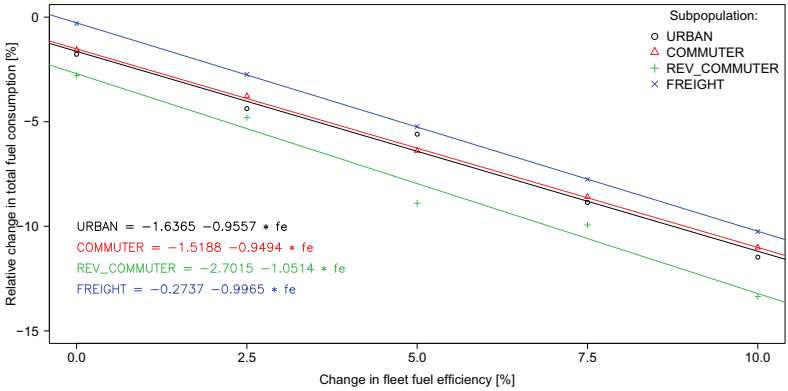


Figure 5.9: Impacts of fuel efficient cars on fuel reduction: parametric estimates by subpopulation.

in fuel efficiency. Fig. 5.9 shows simulation results of relative changes in total fuel consumption over five different levels of fleet fuel efficiency.[17] Level 0.0% is equivalent to the short term reactions (Internalization policy) presented in Sec. 5.4: users are not able to buy more fuel efficient cars. Level 2.5% to 10.0% imply that the whole vehicle fleet is 2.5% to 10.0% more fuel efficient, meaning that users *on average* buy x% more fuel efficient cars as a reaction to the Internalization policy. Fig. 5.9 also provides regression functions for the data points of every subpopulation. As one can nicely see for freight traffic, which is only allowed to adjust routes, the short term re-routing reaction to the Internalization policy at level 0.0% leads to a relative reduction in fuel consumption of −0.2737%. On top of this effect, the increase in fuel efficiency leads to an almost proportional reduction in total fuel consumption as the slope of the regression function indicates (1% higher fuel efficiency leads to −0.9965% less consumption). Urban travelers and commuters react more sensitively to the Internalization policy since they are additionally allowed to change to public transit. This is depicted by the stronger change in total fuel consumption at level 0.0% (urban: −1.6365%, commuter: −1.5188%, reverse commuter: −2.7015%). For urban travelers and commuters, a change in fleet fuel efficiency leads

[17] Please note that the parametric estimates also take into account second order effects in the sense that higher fuel efficiency lowers the optimal toll; compared to the short term reactions at level 0.0%, this leads in the present model to a modal shift towards car and longer distances traveled.

to a slightly under-proportional reduction in fuel consumption, reflecting the second order effects of shifting back to car and to longer distances. For reverse commuters, this effect is not found.

Now, the long-term effect of changes in the vehicle fleet can be determined approximately as follows: Erath and Axhausen (2010) predict an average change in fleet fuel efficiency of 5% as a reaction to an average fuel price increase of 100%. As Tab. 5.4 indicates, the average price increase per vehicle kilometer including CO_2 between the base case and the Internalization policy is roughly 10% for urban travelers and commuters (2.25 to 2.71 $EURct/km$ on top of the monetary distance costs of 30 $EURct/km$). Following Erath and Axhausen (2010), an increase in the vehicle fleet emission efficiency of 0.5% is assumed. In addition, it is assumed that more fuel efficient cars are not more expensive than normal cars and, thus, changing the vehicle does not imply any additional investment. Using the regression function from Fig. 5.9, a 0.5% increase in the vehicle fleet fuel efficiency would lead to additional changes in total fuel consumption. Thus, some additional changes in total fuel consumption are expected due to long-term adjustments in the vehicle fleet. These occur on top of the short-term effect; the differences to the assumed 0.5% increase in the vehicle fuel efficiency are, however, relatively small. One can therefore state that accounting for car ownership decisions would only have a minor impact on the results obtained in this chapter. The reason could be that the price signal of the Internalization policy is not strong enough to significantly change long-term route choice and mode choice behavior.

5.6 Summary

In this chapter, a new simulation approach was presented to internalize external air pollution costs for a real-world large-scale scenario using an agent-based model. The resulting exhaust emission and welfare effects were used as a benchmark for the evaluation of a regulatory measure—a speed limitation to 30 km/h in the inner city of Munich. The main methodological contribution was the calculation of a high-resolution first-best air pollution toll in a real-world scenario. This comprised, on the one hand, the implementation of a module that evaluates different alternatives of every agent for the choice model. On the other hand, a router module which is needed for the calculation of time-dependent least cost paths through the network. Both modules account for individual vehicle attributes and time-

dependent traffic states. Since agents additionally interact in the physical environment of the network, the resulting toll is equal to agent-specific MSC in terms of vehicle attributes and congestion-based emissions.

In terms of absolute emissions, the highest share is contributed by freight, followed by commuters. Urban travelers have a minor impact even though they represent almost 70% of the total population. When comparing the regulatory measure to the emission cost Internalization policy, it is found that the regulatory measure is considerably less successful in terms of total emission reduction. It reduces emissions of urban travelers more than the first-best solution, while even increasing the emissions of commuters and freight, both leading to a increase in deadweight loss. That is, the regulatory measure leads to higher market inefficiencies than a 'do-nothing' strategy: generalized prices beyond the economic optimum for urban travelers, generalized prices below the economic optimum for commuters and freight. The Internalization policy increases welfare for all subpopulations, even without the benefits from reduced emissions. That is, the toll implicitly reduces congestion and therefore also works as a congestion pricing scheme. Additionally, it is likely to have further positive effects on welfare, e.g. by reducing noise emissions or increasing property values.

Additionally, a geographical mapping of changes in user benefits back to each person's home location was performed. This points out the advantage of the multi-agent approach and allowed to compare the two policies in a more detailed manner: While the Zone 30 policy leads to welfare losses mainly in and around the regulated zone, the Internalization policy (without a redistribution of toll payments) yields gains and losses all over the city area. However, the overall welfare level is found to be higher than with the Zone 30. With a redistribution of toll payments, the Internalization policy leads to an overall welfare gain throughout the city area.

Furthermore, the analysis of the simulated first-best air pollution toll showed that the resulting average emission costs per vehicle kilometer are very close to estimates in the literature. However, neither the emission tolls nor the estimates from the literature do reflect marginal costs with respect to damage of human health since they do not differentiate among the number of individuals that are exposed to a certain pollution concentration. Introducing a correction term might improve the emission and welfare effects of the Zone 30 policy. For this reason it is planned to model the whole impact-path-chain of air pollution which implies an exposure analysis of the whole population and a monetization of these effects.

Because of the simplified way of generating freight demand and modeling its behavioral reactions, the total emissions of freight are presumably even higher than in this chapter. Additionally, for the Internalization policy, this chapter is likely to underestimate the toll payments of freight, as well as the positive welfare change after redistribution. This clearly shows that there is a strong need for research that aims at improving demand and behavioral modeling of freight transport.

The final discussion on long-term changes to the vehicle fleet shows that there are additional changes in total fuel consumption and emissions when assuming that travelers react to the Internalization policy by buying more fuel efficient cars. However, because of the rather weak price signal, this is not found to significantly change long-term route and mode choice decisions.

In principle, the approach presented in this chapter allows the evaluation of any regulatory policy. Here, the goal was to present the methodology by means of a fictive speed limitation in the inner city. Other (maybe more realistic) policies come to mind, for example speed limitations or pricing schemes on certain road categories. After solving some of the issues related to freight traffic, the appraisal of these policies provides interesting venues for more practical research in the future. A first step into this direction is a recent paper by Hülsmann et al. (2013), who, in a similar scenario, price roads with high emission concentrations.

Another important, even though more practical contribution of this chapter is the following: it could be demonstrated that the simulation of first-best emission tolls is possible in a real-world setup and that it could be used as a benchmark for second-best policies. This seems to be highly relevant for politicians and decision makers.

Chapter 6

Conclusion

The goal of this thesis was to identify improvements in applied Benefit-Cost Analysis (BCA) that can be obtained when introducing heterogeneous user preferences and user attributes into an agent-based transport simulation. After formulating six Research Questions in the introductory Ch. 1, reviewing literature and developing the methodology in Ch. 2, several hypothetic policies were introduced as Case Studies in different real-world scenarios. In Ch. 3, the focus was on heterogeneous user preferences. The heterogeneity was expressed by an income-dependent marginal utility of money in every individual's utility function. Ch. 4 and Ch. 5 focused on heterogeneous user attributes which was captured by person-specific vehicle attributes, resulting in person-specific exhaust emissions. In the Case Studies, changes in mobility patterns, exhaust emissions, and well-being of individuals were calculated in order to answer the Research Questions of this thesis. This final chapter now summarizes the main research contributions and presents answers to the Research Questions. It closes the thesis with an overall summary and an outlook on possible future research.

6.1 Research Contributions

6.1.1 Heterogeneity in User Preferences

This thesis started with the development of a novel approach where heterogeneous user preferences from survey data—expressed by an income-dependent marginal utility of money—were introduced in the behavioral model of an agent-based transport simulation. After testing the the new model in a simple test scenario, it was applied to a large-scale real-world scenario

of the Zurich metropolitan area in Switzerland. Two policies were then introduced: a non-monetary policy with a global increase of the Public Transport (PT) operating speed by 10%, and a monetary policy with a distance-based morning peak toll in the inner city of Zurich. Agents could adapt their mobility behavior with respect to route, mode, and departure time choice. The resulting change in agent's mobility patterns already allows to answer the first Research Question

> "For the *behavioral model* of the transport simulation, what are the advantages and disadvantages of considering heterogeneous user preferences?"

as follows:

- Advantages
  - The results of the base case simulations indicate that user preferences estimated from survey data slightly improve the accuracy of the model at the aggregated level. However, the differences are not very important to a model where the behavioral parameters are simply calibrated against observations. Presumably, this is due to the fact that activity patterns, preferred activity durations, opening times, and transportation network structure are dominating the aggregated results.
  - Nonetheless, when using income-dependent user preferences, one observes choice behavior related to the income level: Values of Travel Time Savings that increase with income capture the higher willingness-to-pay of high-income people for travel time reductions, and thus, by tendency make them choose faster, but more expensive options.
  - Irrespective of heterogeneity in user preferences, one can argue that the use of estimated parameters is needed for modeling empirically justified choice behavior. Elasticities are encoded in these preferences, and thus, the model with estimated parameters yields a better forecast ability on the individual level.
- Disadvantages
  - Obtaining the necessary estimates from Revealed Preference (RP)/Stated Preference (SP) data is time consuming and expensive. Additionally, all attributes of the choice alternatives

that are used for estimation need to be available for each person in the synthetic population; this leads to an interdependence between the estimation and the transport model, putting further restrictions on the estimation: the model that provides the best fit to the RP/SP data might not be applicable due to the lack of data in the transport model. That is, data requirements for the already rather data-intense agent-based models rise even further.

- Additionally, most parameter estimation studies do not explicitly report opportunity costs of time. In the agent-based model of this thesis, necessary assumptions had to be made in order to convert the estimated parameters to the simulation parameters.
- Finally, the question regarding the 'correct' functional form of the utility function(s) arises. As stated above, some functional forms with good fit to the data might already be ruled out beforehand, due to limited data availability in the transport model. The formulation of the utility function additionally influences the results since it depicts in particular effects that the researcher intends to show, e.g. income-dependent choice behavior. This might not always be the dominating influence on choices (Börjesson et al., 2013).

In addition to changes in mobility behavior, changes in utility levels of agents as a result of the two policy measures have been computed on individual level. To the knowledge of the author, there are only few contributions in the literature that have attempted such computations (see, e.g., Franklin, 2006); furthermore there is no such contribution that accounts for multiple choice dimensions simultaneously while dealing with such large numbers of individuals as the present thesis. Additionally, utility changes were aggregated following the income and the time equivalent approach, answering the second Research Question

> "For the subsequent *economic analysis* of policy measures, which impacts does the above model have in case of (a) a non-monetary policy, and (b) the optimization of a pricing policy?"

as follows:

- The resulting individual utility differences are robust figures to identify winners and losers of a transport policy.

- Following the income equivalent approach, road user pricing schemes are—under certain conditions—found to have regressive impacts on the welfare distribution of society. Interestingly, the same is true for non-monetary policies that aim at shortening travel times.
- Therefore, a progressive (income) tax to finance such policies might not be re-distributive since it only reflects the individual willingness-to-pay to improve the service.
- Comparing the income equivalent approach to a valuation via time equivalents and an average VTTS in a parametric optimization of a distance toll leads to different overall welfare levels. Importantly, the choice of the aggregation approach may even change the sign of the welfare effect.
- The attempt of explaining public acceptance issues by comparing the results of different aggregation procedures yields a better understanding of inter-personal distributional impacts of policies. This, in turn, could help designing projects with higher public acceptance if, additionally to the Benefit-Cost Ratio (BCR), other indicators are considered in the decision making process.

Overall, it has been shown that the use of estimated behavioral parameters in an agent-based transport simulation *and* in the subsequent economic evaluation has become possible, even for large-scale scenarios. However, the economic evaluation typically relies on a singular value for the marginal utility of money across all alternatives of an individual. This is often not found empirically and indicates the need of further research. Finally, the potential use of person-specific willingness-to-pay in economic appraisal schemes raises the question whether this approach is desirable from a societal perspective (see later in Sec. 6.2). This is not a technical issue, and a normative discussion is needed since the approach would now not only in theory, but in practice imply a deviation from certain democratic principles (e.g. higher weight for individuals with a higher willingness-to-pay).

6.1.2 Heterogeneity in User Attributes

After investigating the impacts of heterogeneous user preferences on behavioral modeling and economic analysis, this thesis focused on the development of a model that quantifies person-specific exhaust emissions. The underlying

reason is that BCA should meet the requirement to include environmental externalities in addition to the congestion externalities which are implicitly considered in the transport model. The answer to the third Research Question

> "In a large-scale dynamic traffic flow simulation, how can heterogeneous user attributes, such as vehicle type, be used for the calculation of person-specific pollution levels?"

is mostly covered in Sec. 2.2.2, where the technical feasibility of integrating heterogeneous user attributes into an agent-based model is proven. That section presents one possible solution to the problem of calculating highly differentiated warm and cold-start emissions which depend on vehicle type, traffic state, and activity durations. This is done by coupling the traffic flow model of the Multi-Agent Transport Simulation (MATSim) and the vehicle attributes from survey data with the database of the Handbook on Emission Factors for Road Transport (HBEFA) in the Emission Modeling Tool (EMT). Emissions are calculated every time a traveler leaves a road segment, and whenever she starts the engine. The novelty of the approach is that a calculation of time-dependent vehicle-specific emissions becomes feasible for large-scale real-world scenarios. There are only few contributions in the literature that attempted this (see, e.g., Hatzopoulou and Miller, 2010, who also use MATSim as traffic flow model); in contrast to their model, the emissions calculated in this thesis are vehicle-specific and the approach does not assume fixed emissions per time unit. Since HBEFA provides data for many European countries, the model can easily be transfered to any scenario in Europe.

After making the emission tool operational, it was investigated whether the person-based approach improves the understanding of the interaction between car travel demand and emission level. This was tested for the metropolitan area of Munich, Germany. Thus, the answer to Research Question four

> "Given a price change in car user costs, are aggregated price elasticities of emissions higher than those for car travel demand? If yes, can a spatially disaggregated effect be observed?"

can now be given as follows:

- Yes, price elasticities of emissions turn out to be higher than those of demand. For the scenario under consideration, the latter were

found to be in a reasonable range. Two possible reasons for this effect were identified: First, travelers with long car trips (with higher speed and, thus, higher emissions per vehicle kilometer) are over-proportionally changing to PT. This is referred to as *biased mode switch effect*. Second, in urban areas, travelers are driving faster on formerly congested roads. This is referred to as *congestion relief effect*.

- In a spatially disaggregated analysis, areas with high potential for emission reduction turn out to be the areas with initially high travel demand. On high-speed arterials and tangential motorways, absolute emissions and travel demand are reduced. However, average emissions per vehicle kilometer rise because of higher speeds. This effect decreases the efficiency of the system in terms of emissions per vehicle kilometer. In contrast, most urban areas show less emissions per vehicle kilometer where travel demand is reduced. This effect, in turn, increases the efficiency of the system with regards to kilometer specific emissions. Both effects result from congestion relief. It can therefore be summarized that the EMT captures the effect of an emission optimal speed around 60 km/h.

6.1.3 Heterogeneity in External Cost Pricing

Starting from the output of the EMT, a new approach was developed to calculate vehicle-specific, time-dependent, first-best air pollution tolls for the Munich scenario. The tolls were obtained by coupling the exhaust emission values with cost factors from Maibach et al. (2008). Thus, the answer to Research Question five

> "In an agent-based large-scale transport simulation, how can the internalization of external air pollution costs be modeled on an individual level?"

is already given in Sec. 5.2.3, which shows that two modules in the agent-based transport model needed to be modified: First, the router module, which provides time-dependent least (generalized) cost paths through the network, now calculates different routes for every agent since the generalized costs are dependent on the agent's vehicle information and expected traffic states in the network. Second, the scoring module, which evaluates the choices of every agent, additionally considers money payments that depend

on the agent's vehicle information. These payments are triggered every time an agent leaves a road segment.

The main contribution of the internalization approach is the calculation of tolls that are equal to vehicle-specific Marginal Social Costs (MSC) in terms of vehicle attributes and congestion-based emissions. To the knowledge of the author, there is no contribution in the literature that has attempted such calculation so far. When aggregating these first-best emission tolls to an average monetary value of damage to society, it appears that this value is very close to damage cost estimates in the literature. That is, the emission tool combined with cost factors from Maibach et al. (2008) seems to produce correct toll levels.

Since first-best tolls can be seen as a rather theoretical concept, the results in traffic conditions and economic effects were compared to the impacts of a regulatory measure—a speed limitation to 30 km/h in the inner city. This comparison shows that the regulatory measure is considerably less successful in terms of total emission reduction. It even leads to higher inefficiencies than a 'do nothing' strategy. That means generalized prices beyond the economic optimum for urban travelers, and generalized prices above the economic optimum for commuters and freight traffic. Additionally, it was shown that the emission toll implicitly reduces congestion and therefore also works as a congestion pricing scheme. In that sense, the answer to Research Question six

> "Does the economic analysis of a simulated first-best air pollution toll improve the evaluation of regulatory measures?"

is the following:

Yes, the approach can be used to generate a benchmark for the evaluation of transport policies that aim at reducing air pollution in metropolitan areas. It shows a theoretical maximum in efficiency gains that could be obtained by policy interventions. Looking at all relevant indicators such as changes in mobility patterns, exhaust emissions, and welfare distribution allows to compare real-wold policies to that benchmark. A geographical mapping of changes in user benefits to each person's home location emphasizes the advantage of the multi-agent approach. The impacts of the two policies could be compared in a more detailed manner or giving additional indicators about the spatial effects of different redistribution schemes of the toll payments. This has been formulated as a need for advances in transport policy appraisal e.g. by OECD (2006). However, the methodology is not fully

developed: a correction term would need to be included in the calculation of the toll level that reflects exposure to an emission concentration, and thus, an estimation about the real damage costs. This is likely to improve the economic evaluation of a Zone 30 policy.

6.2 Summary and Outlook

This thesis highlighted several structural issues in the context of current quantitative economic policy appraisal. By means of several Case Studies, it has shown how advances in multi-agent transport models could provide valuable additional information for decision makers as well as for public participation processes. The thesis did not concern adding new elements to theoretical research in the area of transportation science, but rather making well-known theories operational while still being applicable for large-scale scenarios. That means, the strength of this thesis is the seamless integration of the behavioral model of the transport simulation and the subsequent economic evaluation. Using theoretically well-founded models, the integration has been successfully implemented for two large-scale scenarios with a large number of individuals who perform activity chains in large networks. Furthermore, the approach is taking into account different choice dimensions, namely route choice, mode choice, and departure time choice.

The introduction of *heterogeneous user preferences* in Ch. 3 may capture people's mobility behavior more accurately; however, the question on how to weigh gains and losses of individuals, and how to aggregate those for different individuals, remains a normative one. Findings from research in this field can not directly be converted into policy recommendations, as the following citation by Grant-Muller et al. (2001, p.258) shows on the question how to harmonize policy appraisal schemes in the European Union (EU):

> "[...] all projects [...] are subject to a standard form of appraisal so that priorities can be determined for the use of scarce funding resources. This raises philosophical and practical problems encapsulated in the phrase 'whose values?'. Should local values be used, should they reflect the willingness to pay of the consumers affected? Or should pan-European values be used? Is there a need, in this case, for complete harmonization of investment appraisal of projects of European interest? The answers do not

> lie in the technical arena. As with many appraisal questions, the detail is in the politics."

The advantage of the approach presented in this thesis is that different indicators can be provided for such decisions, and the impact of these decisions on individuals and the society as a whole becomes directly visible.

With the introduction of *heterogeneous user attributes* in Ch. 4, the approach additionally considers air pollution as non-congestion externalities on the single-agent level. Various questions concerning environmental hotspots, or the identification of subpopulations with high emission levels can be answered. Additionally, the approach was shown to allow for rather straightforward geo-spatial or inter-personal winner-loser analyses.

Internalizing these non-congestion externalities in the same evaluation procedure in Ch. 5 showed that the resulting changes in external costs are by a factor of 100 lower than the implicit gains from travel time savings. As found in most project evaluations in practice, they do therefore not play a major role for the BCR, or have a major influence on project rankings. One could argue that the monetization of environmental externalities via willingness-to-pay, hedonic pricing, estimated avoidance or damage costs is not covering the whole effect, and hence, is not comparable to time gains in the same evaluation procedure. Damage costs are potentially a good option for monetary valuation, but they are hard to estimate because of the complex and long-term cause and effect chain (OECD, 2006). Avoidance costs are easier to estimate but require normative goals, e.g. leading to thresholds.

When entering the grounds of normative goals, also backcasting approaches (see, e.g., Geurs and van Wee, 2000; IWW et al., 1998) come to mind. The justification of this idea lies in the fact that individuals possibly have *the right* to a future state of the environment (OECD, 2006). In order to reach a certain (emission) goal by a certain time in the future, backcasting approaches might indicate a need for strong and expensive policy interventions on the transport market. In consequence, avoidance costs would become much higher than e.g. damage costs. It appears that substantial research is required in that area. Investigating the scale differences in external unit costs between time savings and other externalities is possibly one of the most challenging questions in theoretical and applied research on economic appraisal schemes.

In addition to the more general questions above, possible venues for further research have been pointed out in several places of the thesis. Most

are also listed in Sec. 1.3.4. Now, to conclude this thesis, the following list of research opportunities focuses on topics that were treated in the previous chapters:

- *Behavioral Modeling*: It would be helpful to enrich the database of RP/SP surveys so that different subpopulations can be modeled with different VTTS. The income-dependent approach in Ch. 3 showed that it is technically feasible to model diversity in the VTTS within one population. However, as pointed out in Ch. 5, better (behavioral) models for freight are needed where also the Value of Travel Time Reliability (VTTR) might play a role (Wigan et al., 2000). Additionally, there is a need for (mode) choice experiments that are able to separately extract the marginal utility of time as a resource and the additional (dis)utility of traveling (Jara-Díaz, 2007).

- *Economic Appraisal*: Several issues need to be solved in this area: First, it has been discussed in Ch. 2 that a conversion of utility into money terms via income equivalents requires a uniform marginal utility of money across all alternatives of an individual. This necessary convention puts limitations on preference estimation. It might, however, be possible design choice experiments to separately estimate the marginal utility of money and the additional (dis)utility of the purpose of the expense similar to the approach for time above. Second, using the standard MATSim approach for choice set generation might yield incomplete choice sets and correlated plans. The first shortcoming should be addressed in the future by generating more heterogeneous options in the choice set generation. For a fist attempt in route choice for PT and car, see Nagel et al. (2014) and Moyo Oliveros (2013), respectively. The second shortcoming should be solved by improving the implementation for plans removal: not the worst plan should be removed when the maximum number of plans of an agent is reached, but the approach should account for similarities of plans, e.g. by comparing route, mode, or departure times. Hence, following a 'pathsize logit' model, similarity measures need to be defined which impose an additional disutility on similar plans (Ben-Akiva and Bierlaire, 1999; Frejinger and Bierlaire, 2007; Prato, 2009). For a first attempt in the MATSim framework, please refer to Grether (2014). It needs to be tested carefully how such implementations reduce the correlation

structure of plans and how this influences simulation results, including the logsum values for economic evaluation.

- *Emission Modeling*: The EMT proved to produce reasonable results. The software is properly tested and is a potential candidate to become a MATSim contribution to be used by other researchers. It is therefore planned to apply the software to other scenarios in order to eliminate potential remaining use-case specific particularities. In order to capture the full impact-path chain of air pollution damage to human health, there is an interesting branch of research that deals with air pollution exposure. This could in the future also be considered within the current framework, especially since MATSim provides the activity locations and durations of individuals. A first attempt into this direction is a recent paper by Hülsmann et al. (2013), where air pollution concentration is calculated for a small area in Munich based on the output of the EMT. It will, however, be a challenging task to find a model for exposure modeling that produces reasonable air pollution concentrations, but is still applicable to large-scale scenarios. Some work in this field has recently been presented by Kickhöfer and Kern (2014).

- *Pricing and Benchmarking*: Ch. 5 presented an approach how fist-best air pollution tolls can be used in order to evaluate other, e.g. regulatory, measures. Hence, an interesting venue for future research would be to include other negative externalities in the toll calculation, such as noise emissions and congestion in the PT and in the car mode. There exist already prototypes to include these externalities in the MATSim framework, developed by Gerike et al. (2012), Kaddoura et al. (2014, forthcoming), and Kaddoura and Kickhöfer (2014), respectively. The challenge will now be to combine them for a unified toll calculation.

Appendix A

Mathematical Supplements

A.1 Calculation Of Free Flow and Stop&Go Distances

This section describes the mapping of dynamic traffic flows of Multi-Agent Transport Simulation (MATSim) to two traffic states of the Handbook on Emission Factors for Road Transport (HBEFA) 'free flow' and 'stop&go'. The following parameters are needed for the calculation: The link length l in km from the network, a stop&go speed v_s in km/h from HBEFA road type, a free flow speed v_f in km/h from the network, and the average speed on the link $v = \frac{l}{t}$, calculated from network data and link travel time t in the simulation. Since HBEFA emission factors are given in g/km units, there is a need to determine the distance a car is driving in free flow traffic state (l_f), and the distance a car is driving in stop&go traffic state (l_s). Clearly, the sum of these distances is defined by the total link length:

$$l = l_f + l_s \tag{A.1}$$

At the same time, the overall link travel time t needs to be the sum of the time spent in free flow traffic state (t_f) and the time spent in stop&go traffic state (t_s):

$$t = t_f + t_s \ , \tag{A.2}$$

where $t_f = \frac{l_f}{v_f}$, and $t_s = \frac{l_s}{v_s}$. The distance spent in stop&go traffic state is then calculated as follows, the distance spent in free flow traffic state then results from Eq. A.1:

$$
\begin{aligned}
l_s &= t_s v_s && \text{(A.3)}\\
&= (t - t_f) v_s \\
&= (t - \frac{l_f}{v_f}) v_s \\
&= (t - \frac{l - l_s}{v_f}) v_s \\
l_s &= (\frac{l}{v} - \frac{l - l_s}{v_f}) v_s && \text{(A.4)}\\
\Leftrightarrow \frac{l_s}{v_s} &= \frac{l}{v} - \frac{l - l_s}{v_f} \\
\Leftrightarrow \frac{l_s}{v_s} &= \frac{l}{v} - \frac{l}{v_f} + \frac{l_s}{v_f} \\
\Leftrightarrow \frac{l_s}{v_s} - \frac{l_s}{v_f} &= \frac{l}{v} - \frac{l}{v_f} \\
\Leftrightarrow l_s(\frac{1}{v_s} - \frac{1}{v_f}) &= \frac{l}{v} - \frac{l}{v_f} \\
\Leftrightarrow l_s(\frac{v_f - v_s}{v_s v_f}) &= \frac{l(v_f - v)}{v\ v_f} \\
\Leftrightarrow l_s &= \frac{l(v_f - v)}{v\ v_f}\ \frac{v_s v_f}{v_f - v_s} \\
\Leftrightarrow l_s &= \frac{l\ v_s(v_f - v)}{v(v_f - v_s)} && \text{(A.5)}
\end{aligned}
$$

A.2 Spatial Averaging for Visualization

For the spatial representation of local impacts of policy measures in Sec. 4.4.2, Sec. 5.4, a spatial averaging technique with a Gaussian distance weighting function is used. For that purpose, the weight $w_{i,j}$ of every location i for each cell j is computed:

$$w_{i,j} = e^{\frac{-r^2}{R^2}}\ , \tag{A.6}$$

where r is the distance between the location's coordinate and the cell's center coordinate, and R is the smoothing radius of the a three-dimensional Gaussian distribution. In the applications mentioned above, there are

$j = 160 \cdot 120$ cells, defining a regular grid of 19'200 cells. The influence of location-specific values $x_{i,j}$ on every cell j is then calculated by

$$x_{i,j} = w_{i,j} \cdot x_i \ . \tag{A.7}$$

When calculating the *value per area unit* in each cell, the sum of weighted values $\sum_i x_{i,j}$ needs to be normalized to the sum of weights under the Gaussian distance weighting function. This sum of weights A is calculated as follows:

$$\begin{aligned} A &= \int_0^{2\pi} d\varphi \int_0^{\infty} dr \left(r \cdot e^{\frac{-r^2}{R^2}} \right) && \text{(A.8)} \\ &= 2\pi \int_0^{\infty} dr \left(\left(-\frac{R^2}{2} \right) \left(-\frac{2}{R^2} \right) \cdot r \cdot e^{\frac{-r^2}{R^2}} \right) \\ &= 2\pi \cdot \left(-\frac{R^2}{2} \right) \cdot \int_0^{\infty} dr \left(\left(-\frac{2}{R^2} \right) \cdot r \cdot e^{\frac{-r^2}{R^2}} \right) \\ &= -\pi R^2 \cdot \left[e^{\frac{-r^2}{R^2}} \right]_{r=0}^{\infty} \\ &= -0 + \pi R^2 e^0 \\ &= \pi R^2 && \text{(A.9)} \end{aligned}$$

Please note that the above technique is only valid for *summable* variables, such as emissions, vehicle kilometer, welfare, etc. For non-summable variables (e.g. emissions per vehicle kilometer), the sum of weighted values $\sum_i x_{i,j}$ needs to be calculated for both variables (i.e. emissions *and* vehicle kilometers). The quotient of these sums of weighted values then represents an average value for cell j. The normalization with A cancels out.

A.3 Calculation Of User Benefits

As described in Sec. 2.3.2, a common method of measuring user welfare in economics is the logsum term or Expected Maximum Utility (EMU). For the calculation of the individual utility level in units of utility, it is defined as follows:

$$logsum = EMU = \frac{1}{\mu} \cdot ln \sum_{p=1}^{P} e^{\mu V_p} \ , \tag{A.10}$$

Since $e^{\mu V_p}$ often results in large numbers and therefore might become computationally unstable, a different calculation is applied in this thesis—using the utility of the option with the highest benefit $\tilde{V} = \max(V_1, .., V_P)$. The proof of equality is as follows:

$$\tilde{V} + \frac{1}{\mu} \cdot ln \sum_{p=1}^{P} e^{\mu\left(V_p - \tilde{V}\right)} \tag{A.11}$$

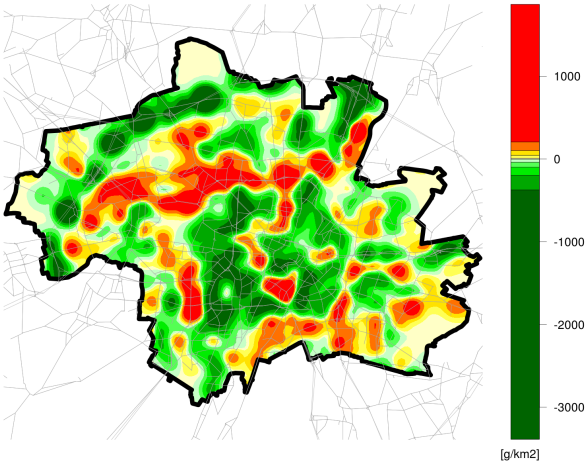
$$\begin{aligned}
&= \tilde{V} + \frac{1}{\mu} \cdot ln \sum_{p=1}^{P} \left(e^{\mu V_p} \cdot e^{-\mu \tilde{V}} \right) \\
&= \tilde{V} + \frac{1}{\mu} \cdot ln \left(e^{-\mu \tilde{V}} \sum_{p=1}^{P} e^{\mu V_p} \right) \\
&= \tilde{V} + \frac{1}{\mu} \cdot \left(ln \left(e^{-\mu \tilde{V}} \right) + ln \sum_{p=1}^{P} e^{\mu V_p} \right) \\
&= \tilde{V} + \frac{1}{\mu} \cdot \left(-\mu \tilde{V} \right) + \frac{1}{\mu} \cdot ln \sum_{p=1}^{P} e^{\mu V_p} \\
&= \frac{1}{\mu} \cdot ln \sum_{p=1}^{P} e^{\mu V_p} \ .
\end{aligned} \tag{A.12}$$

Appendix B

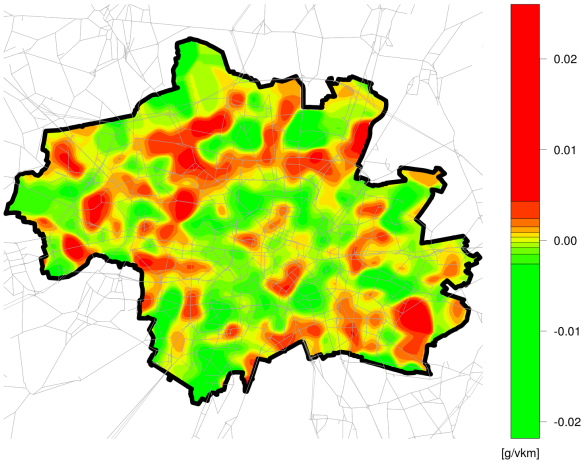
Visual Supplements

B.1 Internalization: Changes in absolute emission levels

In the same manner as Fig. 5.5 for the Zone 30, Fig. B.1 depicts absolute changes in Nitrogen Dioxide (NO_2) emissions for the Internalization policy. As Fig. B.1(a) shows, absolute emissions drop in many places, e.g. within the inner ring road and on the tangential motorway in the north-west of the city. However, also some areas with an increase in emissions can be observed, mainly along the northern part of the inner ring road. In terms of emissions per vehicle kilometer, Fig. B.1(b) does not show a very strong spatial effect. This is presumably due to the fact that the Internalization policy is in contrast to the Zone 30 not a geographically limited measure. However, a comparison of the two figures in the present section gives the impression that emissions per vehicle kilometer tend to increase where overall emissions increase. And emissions per vehicle kilometer tend to decrease where overall emissions decrease. That is, with the Internalization policy, the two effects are pointing into the same direction. This is opposite to what has been observed within the regulated zone in Sec. 5.4.1.2.



(a) Absolute changes in NO_2 emissions



(b) Absolute changes in NO_2 emissions per vehicle kilometer

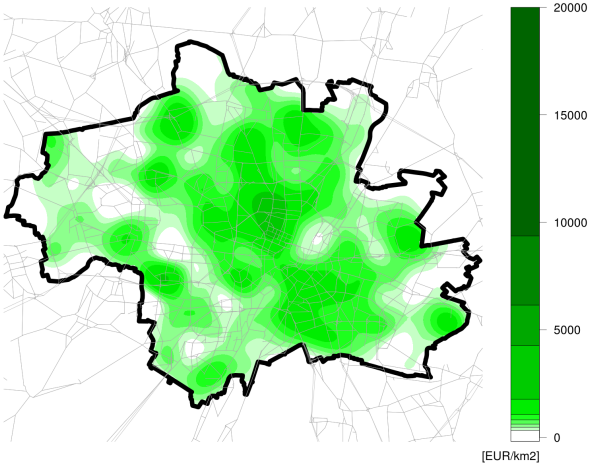
Figure B.1: Internalization: Absolute changes in NO_2 emissions. Plots based on spatial averaging for all road segments. Values scaled to a 100% scenario.

B.2 Internalization: Redistribution of toll payments

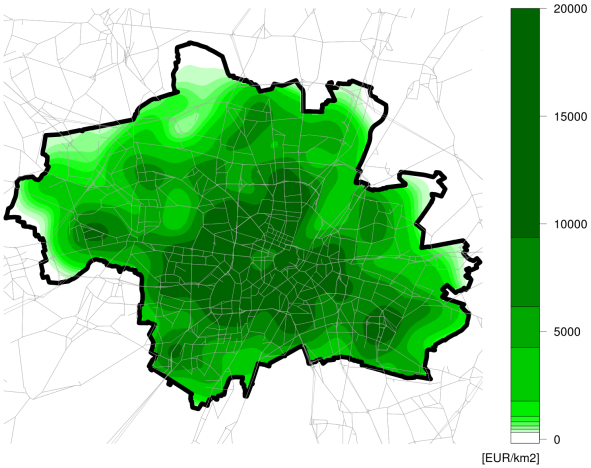
This thesis does not concern an extensive discussion on how toll payments need to be treated in economic policy appraisal. A good starting point on the ongoing discussion of this topic is a paper by Small (1992). However, it seems clear that toll payments are transfer payments from the user to the state or to the local authority, and that these institutions could use the money in a meaningful way in order to increase social welfare. The literature often proposes a subsidy of Public Transport (PT) or a tax refund (see, e.g., de Borger and Proost, 2010). But one could also think of investing the revenues into education, sport opportunities or other public sector responsibilities.

In order to compare the impacts of the Internalization policy with the values in Fig. 5.7(b), Fig. B.2(a) depicts individual welfare levels with the following redistribution scheme: The toll payments of each individual are redistributed to that individual. That is, individuals *behave* as if they had to pay the tolls, but they are reimbursed with the same amount. As one can see, the areas now disappear where the Internalization policy had a negative impact on user benefits (Fig. 5.7(b)). That is, the individual redistribution offsets any negative effect in the boundaries of Munich. The resulting gains are purely because of efficiency gains in the transport system (e.g. less congestion, as discussed in Sec. 5.4.2.1.

Fig. B.2(b) shows the same changes in absolute user benefits, but this time with a lump-sum redistribution of toll payments. Presumably, this approach is more realistic than a person-by-person redistribution, and is also more coherent with the literature. One notices a much stronger impact of the redistribution on individual welfare levels than in Fig. B.2(a): some areas gain up to 20'000 EUR/km^2. Clearly, both figures implicitly contain the population density. The explanation for the difference needs therefore to be found in the construction of the toll and in the distribution of demand: The plots mainly contain home locations of urban travelers, reverse commuters, and some of freight. Commuters live outside of these boundaries, and also many origins of freight trips are outside of that area. Consequently, a lump-sum toll redistribution per capita redistributes the revenues towards areas with high population density, and towards individuals that did not or pay only little toll. This is the effect that can be observed when comparing the two plots in this section.



(a) Individual redistribution



(b) Lump-sum redistribution

Figure B.2: Internalization: Changes in absolute user benefits with different redistribution schemes of toll payments. Plots based on spatial averaging for all home locations. Values scaled to a 100% scenario.

List of Units and Acronyms

AUD Australian Dollar.

CHF Swiss Franc.

CO_2 Carbon Dioxide.

EURct Euro cent, 1/100 *EUR*.

EUR Euro.

NMHC Non-Methane Hydrocarbons.

NO_2 Nitrogen Dioxide.

NO_x Nitrogen Oxides.

PM Particular Matter.

SO_2 Sulfur Dioxide.

USDct US Dollar cent, 1/100 *USD*.

USD US Dollar.

g Gram, 1/1000 *kg*.

h Hour, 60 *min*.

kg Kilogram, the SI base unit of mass.

km Kilometer, 1000 *m*.

mU Money Unit, a unit of money.

min Minute, 60 *sec*.

m Meter, the SI base unit of length.

sec Second, the SI base unit for time.

ton Ton, 1000 *kg*.

util Util, a unit of utility.

vkm Vehicle Kilometer, a unit of transport service provided.

ARTEMIS Assessment and Reliability of Transport Emission Models and Inventory Systems, a harmonized emission model in the European Union, possibly a predecessor of HBEFA, version 3.1. 40, 171

ASC Alternative Specific Constant. 15, 48, 65, 98, 122, 171

BCA Benefit-Cost Analysis. xiii–xv, 1–5, 7, 9, 17, 19, 21–24, 27, 29, 44, 45, 51, 90, 92, 151, 155, 171

BCR Benefit-Cost Ratio. xiv, 2, 25, 27, 154, 159, 171

EMT The Emission Modeling Tool developed in this thesis. xiv, xv, 38–40, 96, 99, 111, 119, 122, 155, 156, 161, 171

EMU Expected Maximum Utility. 50, 165, 171

ERDF European Regional Development Funds, see `http://ec.europa.eu/regional_policy/thefunds/regional/index_en.cfm`; last access: 19.09.2013. 25, 171

EU European Union. 25, 52, 158, 171

HBEFA Handbook on Emission Factors for Road Transport, version 3.1, see `www.hbefa.net`. 11, 38–44, 99, 103, 115, 122, 125, 127, 141, 155, 163, 171

JAVA JAVA programming language, see `www.java.com/`. 99, 123, 171

MATSim Multi-Agent Transport Simulation, see `www.matsim.org`. ix, 9–15, 30–33, 37, 38, 40–44, 47, 48, 50, 51, 55, 61, 62, 66, 73, 95–105, 118–125, 133, 141, 145, 155, 160, 161, 163, 171

MCM A MATSim re-planning module. 36, 70, 75, 82, 104, 127, 171

MiD 2002 Mobility in Germany. A household-based travel diary survey, see `http://mobilitaet-in-deutschland.de/03_kontiv2002/index.htm`, last access 12.02.2014. 101, 126, 171

MIMOSA A macroscopic emission model. 39, 171

MNL Multinomial Logit. 15, 38, 47, 48, 50, 62, 70, 89, 97, 108, 120, 171

MOVES Motor Vehicle Emission Simulator, see `http://www.epa.gov/otaq/models/moves/`. 39, 171

MPC Marginal Private Costs. 8, 117, 171

MSC Marginal Social Costs. 8, 117, 148, 157, 171

NPV Net Present Value. 25, 171

NUTS Nomenclature of Statistical Territorial Units, see `http://epp.eurostat.ec.europa.eu/portal/page/portal/nuts_nomenclature/introduction`, last access 18.02.2011. 102, 171

PHEM Passenger car and Heavy-duty Emission Model. 39, 171

PT Public Transport. 14, 32, 34, 51, 56, 61, 64–80, 82, 85, 91, 93, 99, 122, 127–129, 132–134, 152, 156, 160, 161, 169, 171

RCM A MATSim re-planning module. 36, 75, 82, 104, 127, 171

RP Revealed Preference. 6, 64, 152, 153, 160, 171

RUM Random Utility Model. 17, 19, 46, 50, 171

SP Stated Preference. 6, 64, 101, 125, 152, 153, 160, 171

SROI Social Return On Investment. 20, 23, 171

SUE Stochastic User Equilibrium. 36, 171

TCM A MATSim re-planning module. 37, 70, 75, 82, 171

VISSIM Verkehr In Städten – SImulationsModell, see `www.ptv.de`. 39, 171

VISUM Verkehr In Städten – UMlegung, see `www.ptv.de`. 100, 171

VTTR Value of Travel Time Reliability. 15, 160, 171

VTTS Value of Travel Time Savings. xi, 15, 25, 27, 29, 48, 49, 52, 55–57, 60, 66, 86, 88, 90, 92, 93, 98, 117, 121, 122, 143, 144, 152, 154, 160, 171

XML Extensible Markup Language, see `www.w3.org/XML/`. 43, 99, 123, 171

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