How much do incentives affect car purchase? Agent-based microsimulation of consumer choice of new cars—Part I: Model structure, simulation of bounded rationality, and model validation

Michel G. Mueller, Peter de Haan*

ETH Zurich, Institute for Environmental Decisions, Natural and Social Science Interface, Universitaetstr. 22, CHN J 73.2, 8092 Zurich, Switzerland

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ABSTRACT
This article presents an agent-based microsimulation capable of forecasting the effects of policy levers that influence individual choices of new passenger cars. The fundamental decision-making units are households distinguished by sociodemographic characteristics and car ownership. A two-stage model of individual decision processes is employed. In the first stage, individual choice sets are constructed using simple, non-compensatory rules that are based on previously owned cars. Second, decision makers evaluate alternatives in their individual choice set using a multi-attributive weighting rule. The attribute weights are based on a multinomial logit model for cross-country policy analysis in European countries. Additionally, prospect theory and the notion of mental accounting are used to model the perception of monetary values. The microsimulation forecasts actual market observations with high accuracy, both on the level of aggregate market characteristics as well as on a highly resolved level of distributions of market shares. The presented approach is useful for the assessment of policies that influence individual purchase decisions of new passenger cars; it allows accounting for a highly resolved car fleet and differentiated consumer segments. As a result, the complexity of incentive schemes can be represented and detailed structural changes can be investigated.

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1. Introduction

Two main future challenges are associated with energy use. On the one hand, climate change caused by anthropogenic emissions of greenhouse gases (IPCC, 2007a). On the other hand, energy supply security with increasing energy demand worldwide, diminishing fossil fuel sources, and increasing dominance of a small number of major producers (IEA, 2006). Both the International Energy Agency’s World Energy Outlook 2006 (IEA, 2006) and the Fourth Assessment Report of the Intergovernmental Panel of Climate Change (IPCC, 2007b) draw a picture of urgency and resolve with which action in the policy arena should be taken. IEA (2006) and IPCC (2007b) identify the improvement of new vehicle energy-efficiency as the dominant policy in the transport sector and as an overall key strategy in order to respond to the twin challenges mentioned at the outset.

Significant gains in energy-efficiency of new passenger cars are feasible at an acceptable cost from an engineering point of view (Greene and DeCicco, 2000). Technological advances can be used either to improve energy-efficiency or to increase power and weight (IEA, 2006; IPCC, 2007b). Historic developments of energy-efficiency, weight, and power of new passenger cars show that market forces often favor increases in power and weight (de Haan et al., 2009; Turrentine and Kurani, 2007; Zachariadis, 2006). Government policies can play an important role in promoting energy-efficiency.

Models of car choice predominantly rely on random utility maximization and a rather low level of detail with regard to the choice alternatives; i.e., car types are specified on a vehicle segment level (de Haan et al., 2009; de Jong et al., 2004; Peters et al., 2008). Due to the huge number of individual decision makers involved and alternatives offered, Peters et al. (2008) motivate microsimulation for the assessment of policies that influence individual purchase decisions of new passenger cars. Proceeding with their line of argument, we present an agent-based microsimulation with a highly resolved car fleet and differentiated consumer segments. Furthermore, regarding the individual-level behavioral response to policy measures, there is a robust and compelling body of evidence of the bounds to rationality of actual decision makers; decision processes are often governed by heuristics, cognitive rules of thumb, rather than analytical deliberation (Bettman et al., 1998; Kahneman, 2003).

Van den Bergh et al. (2000) review and highlight the need to explore alternative models of behavior for environmental policy;
e.g., non- and semi-compensatory models have been applied to travel choice modeling (Arentze and Timmermans, 2007; Cantillo and Ortúzar, 2005; Chorus et al., 2008). A central goal of the presented work was to enrich the microsimulation with a behavioral model of consumer decision processes based on the above-mentioned empirical evidence.

This article presents the theoretical background and derivation of a conceptual two-stage model of the decision process (Section 2), its operationalization in and the general structure of the microsimulation (Section 3). In Section 4, the full-scale microsimulation is compared against reduced model versions and actual market observations. Finally, in Section 5, we discuss the methodology, the implications and the limitations of the introduced microsimulation and present our conclusions in Section 6. De Haan et al. (2009) report the results of a concrete application of the microsimulation model.

2. Decision process and car choice

2.1. Consumer choice of new passenger cars

Choice of new passenger cars has received constant attention in the consumer research literature. Considering the high purchase price of a new passenger car, one would expect extensive external search for information and elaborate decision processes. A surprising, yet consistent finding of consumer research is that pre-purchase search activity is limited, even for major consumer durable goods (Beatty and Smith, 1987; Katona and Mueller, 1955; Newman and Staelin, 1972; Olshavsky and Granbois, 1979). Taxonomies of individual search strategies identified distinct external information search patterns and refined the picture of lower-than-expected search effort (Claxton et al., 1974; Furse et al., 1984; Kiel and Layton, 1981; Newman and Staelin, 1973). Furse et al. (1984) hypothesized these strategies to be a result of heuristic decision processes. Another explanation of little explicit search is that information gathering is a continuous process not limited to the actual purchase process (Bloch et al., 1986; Claxton et al., 1974). Punj and Stewart (1983) highlighted the importance of situational and individual characteristics and interaction effects thereof. This focus on characteristics of the decision-maker and his adaptation to the task is in line with the notion of bounded rationality coined by Simon (1955, 1956).

2.2. Rationality and bounded rationality

Discussing the terms rationality and bounded rationality equals walking on a tightrope; their usage is, at least, controversial, as a result of different interpretations across and even within disciplines. Omniscience is an adequate term to describe the neoclassical concept of rationality, assuming perfect information and the capacity to perform complex optimization algorithms. Simon (1955, 1956) pioneered the distinction between perfect and bounded rationality. The concept of bounded rationality embraces the limits of human information-processing capabilities and their need for adaptation to different task environments.

One interpretation of bounded rationality is an extension of the model of the perfectly informed, optimizing individual. If time, knowledge and computational power are limited, optimization needs to account for these constraints (Stigler, 1961; Wilde, 1980). Simon’s work inspired another major research theme, the heuristics and biases approach, prominently advanced by Kahneman and Tversky (Kahneman, 2003; Kahneman and Tversky, 2000). Strongly guided by an analogy of perception, this interpretation of bounded rationality delivered major insights in the areas of heuristics of judgment, risky choice and framing effects (Kahneman, 2003; Tversky and Kahneman, 1981). Applications of this research program’s core ideas to riskless choices revealed its relevance to consumer choice (Thaler, 1999). The need for adaptation of decision behavior to the decision environment and the underlying processes of choice are at the core of the adaptive decision-making approach to the study of consumer choice (Bettman et al., 1998). The foundation of this additional offshoot of bounded rationality is that consumers apply a variety of cognitive processes to decision making.

In order to elicit facets of bounded rationality relevant to financial incentives aimed at influencing new passenger car choice, we adopt an integrative viewpoint, exploring both the adaptive decision-making and the perceptual approach. The adaptive decision-making approach is informative about how consumers use and process information (Subsection 2.3). The perceptual approach reveals much about the perception of monetary values (Subsection 2.4).

2.3. Two-stage model of the decision process

The decision processes underlying consumer choice were shown to be contingent on the complexity of the task, first and foremost determined by the number of alternatives available (Olshavsky, 1979; Payne, 1976). For complex task environments, a consistent finding over a number of studies is the utilization of multistage strategies, namely a two-staged decision process (Bettman and Park, 1980; Olshavsky, 1979; Payne, 1976; Ursic and Helgeson, 1990): a screening stage in which alternatives are eliminated using simple non-compensatory rules, followed by a compensatory evaluation of the remaining alternatives. This distinction between screening and actual choice is in line with image theory (Beach, 1993), in which the importance of prechoice screening of alternatives is analyzed in great detail.

Fig. 1 presents our resulting conceptual model of the decision-making process. It serves as a template for the implementation of choice processes in the microsimulation model in Section 3.

Fig. 1. Conceptual two-stage model of the decision process. The universal choice set is the set of all available alternatives. The choice set is the set of alternatives considered by the decision-maker.
Facets of this approach to bounded rationality relevant to financial incentives are most notably the limited awareness of alternatives of consumers, and the way choice sets are constructed. In a broader scope, this two-stage model reflects the idea of a two-system view of human cognition, distinguishing between intuition and reasoning (Hammond, 1980; Kahneman, 2003; Scholz, 1987). It is related to the widespread notion of dual-process models in social and cognitive psychology (see Chaiken and Trope, 1999, for a collection of dual-process models).

2.4. Prospect theory: perception of monetary values

The best-known contribution of the perceptual approach to bounded rationality is the prospect theory (Kahneman and Tversky, 1979). The cornerstone of prospect theory is that preferences are reference dependent, e.g., the carriers of values are not absolute states but gains and losses relative to a reference point. Additional essential features of prospect theory are loss aversion and diminishing sensitivity (Kahneman and Tversky, 2000). Loss aversion implies that people are more sensitive to losses than to gains of the same magnitude. Diminishing sensitivity states that the impact of incremental gains or losses diminishes as the gains or losses become larger.

The application of prospect theory to consumer choice by Thaler (1999) provides a useful framework for extracting and understanding facets relevant to the mechanics of financial incentives. Consumers evaluate outcomes within mental accounts using the value function known from the prospect theory. Based on the value function, we conclude that financial incentives should be designed so that consumers perceive them separately from the purchase price (in analogy to the argument of Thaler (1985) on coding gains and losses). This argument holds true for both fees and rebates. Additionally, consumers can be expected to be more sensitive to fees than to rebates of the same magnitude.

3. Agent-based microsimulation

3.1. Model structure

The first step in modeling is to determine the type of model most suitable for the task at hand. Brown and Harding (2002) identify a variety of key characteristics on which models for policy analysis differ. Creedy (2001) argues that although there is a role for a variety of alternative models in policy analysis, direct policy advice requires the construction of large-scale simulation models of “low-level” units (e.g., individuals or households). Such microsimulation models are based on large cross-sectional datasets that capture the heterogeneity of the elemental decision-making units. This paradigm for modeling social and economic policies by capturing the structural complexity of the systems and policies being modeled and by basing models on knowledge about elemental decision-making units was pioneered by Orcutt (1957) and Orcutt et al. (1961). Applications of microsimulation models have largely focused on the field of governmental tax and transfer policy (Halpin, 1999); in transportation, agent-based microsimulation has been applied to traffic simulation modeling (Barrett et al., 1995; Raney et al., 2003). An overview on issues of constructing and using microsimulation models and existing model applications can be found in Gupta and Kapur (2000) and Harding (1996). Microsimulation provides a mechanism to capture the complexity of the systems being modeled and to examine the detailed nature of incentive schemes and the resulting structural changes (Creedy, 2001; Brown and Harding, 2002). Hence, we identify microsimulation as the appropriate method for operationalizing the above-mentioned facets of individual purchase decisions.

Microsimulation is closely related to the individual-level modeling approaches of cellular automata and agent-based models. Williamson (2007) suggests that “in their originally conceived forms, these three approaches may be regarded as representing the three corners of a continuum of individual-level modeling approaches”. Pure agent-based models focus on behavioral rules of and interaction between individuals (Williamson, 2007). Our focus on behavioral processes of the individual decision-making unit and the ambition to capture much of the system’s complexity and heterogeneity positions our approach as an agent-based microsimulation, whose structure is depicted in Fig. 2.

Significant evaluations of incentive schemes that influence new passenger car purchase decisions are obtained by comparing the results of a reference run and a policy run. These results are the forecasted new passenger car sales or any aggregated measure thereof. The reference run is a “business-as-usual” simulation run without incentive schemes; the policy run is a simulation run with the incentive scheme to be evaluated in effect. The reference run serves not only as a baseline to which consecutive policy runs are compared, it also yields the agents’ distributions of retention rates, an additional input to the policy run introduced in Subsection 3.5. One cornerstone of the model are the agents, car purchasing entities, and their decision processes which are operationalized following the conceptual two-stage model introduced in Subsection 2.3. The other cornerstone is the input of multiple large-scale datasets. In the following subsections, the model structure is presented by first describing the fundamental input data: the synthetic population of agents (Subsection 3.2) and the universal choice set which contains all available alternatives (Subsection 3.3). The presentation of the agents’ individual decision processes follows the two-stage model: first, the characteristics of the first decision stage are presented; the limited choice set size (Subsection 3.4) and the composition of the choice set (Subsection 3.5). Second, the second choice stage is presented: multi-attributive weighting (Subsection 3.6) which is operationalized by a cross-country discrete choice model (COWI, 2002) and the perception of monetary values (Subsection 3.7). In addition, formal assumptions for modeling that any model requires and imposition of values that inevitably involve a degree of judgment are presented in the course of this section.

3.2. Synthetic population

The car purchasing entities in the presented microsimulation model are representations of private households that purchase exactly one new passenger car; these synthetic households are characterized by selected sociodemographic features and information on car transaction behavior and car ownership. Consequently, the synthetic population should mirror the characteristics of the population of car purchasing households.

The sociodemographic features that characterize the synthetic households correspond to the ones incorporated in the cross-country car choice model for policy evaluation in European countries presented in COWI (2002). The synthetic households are classified into 40 different sociodemographic groups, distinguished by household structure, income level, sex and age of the person purchasing the car (Fig. 2). The proportions of these sociodemographic groups in the synthetic population must be in line with overall Swiss statistics of new passenger car purchasing households. The distribution with regard to the sociodemographic features household structure, income level and age were
behavior and car ownership. Based on de Haan et al. (2006) who holds are characterized by selected information on car transaction model differences in brand preferences specific to these groups. Switzerland. This segmentation is utilized in Subsection 3.6 to the German-speaking (65% of the overall population), the Additionally, each synthetic household is allocated either to based on the expected distribution according to COWI (2002). The sex distribution within the sociodemographic determined based on the Swiss travel behavior micro-census 2000 (BFS, 2001). The sex distribution within the sociodemographic groups was not available for Switzerland and was therefore based on the expected distribution according to COWI (2002). Additionally, each synthetic household is allocated either to the German-speaking (65% of the overall population), the French-speaking (28%), or the Italian-speaking (7%) part of Switzerland. This segmentation is utilized in Subsection 3.6 to model differences in brand preferences specific to these groups. In addition to sociodemographic features, the synthetic households are characterized by selected information on car transaction behavior and car ownership. Based on de Haan et al. (2006) who distinguish five types of vehicle transactions, we identify the distinction between the following two types of vehicle transaction behavior as relevant to our model: replacement purchases and non-replacement purchases, consisting of first-time purchases and stock-increase purchases. Any car purchase of the synthetic households is designated as either one of these two types. De Haan et al. (2006) used a cohort-based model in order to estimate the proportions of the two above-mentioned car transaction types in the Swiss new passenger car market, identifying a share of 77% replacement purchases and 23% non-replacement purchases. To all synthetic households that conduct a replacement purchase, the passenger car that is to be replaced is allocated. The distribution of the parameters make, car size class, transmission type, and fuel type of these cars corresponds to the distribution of the respective parameters of passenger cars replaced by the purchase of a new passenger car in Switzerland in 2005. This distribution was determined by a database of new passenger car transactions in spring 2005. Finally, the synthetic households exclusively represent buyers of private cars. The distinction between private and commercial car buying behavior is widespread in car choice models (COWI, 2002; de Jong et al., 2004). In the concrete application of the microsimulation model in de Haan et al. (2009), commercial car buyers are represented as an additional type of agent whose car choice behavior is governed by the company car choice model described in COWI (2002).

### 3.3. Universal choice set

The universal choice set consists of all new passenger car versions (all unique technological choices with respect to...
make–model, body type, driveline, engine size, fuel type, and transmission type) available for purchase at a given point in time. All technical characteristics were taken from the Swiss vehicle certification database. It comprises a wide array of technical characteristics. However, it does not include information on purchase prices and does not yield reliable information on temporal availability of specific passenger car versions. This information was taken from a commercial data source. The universal choice set was constructed for December 2005, which serves as the base month for the simulation runs presented in this article and in de Haan et al. (2009). The technical characteristics that are available for the resulting 2089 passenger car versions are listed in Fig. 2.

3.4. Choice set size: gamma heterogeneity

Consumers will only evaluate a fraction of the 2089 passenger car versions that are theoretically available. We focus on the two salient questions with regard to screening of alternatives (Subsection 2.3): how many passenger car versions will the choice set consist of, and how are these alternatives composed? We answer these questions directly; by specifying the size of the choice set (this subsection), and by identifying and implementing constraints on the individual choice sets (Subsection 3.5.). Consistent information on the size of consumers’ choice sets is difficult, if not impossible to obtain, due to ambiguous perceptions of the notion choice set. Furthermore, it is questionable that consumers are sufficiently aware of the processes they apply to construct their choice set; attempting to elicit this information is likely to produce unreliable information. Consequently, we construct individual choice sets by randomly drawing alternatives from the universal choice set. It is reasonable to postulate a relationship between the extent of pre-purchase search activity and choice set size. Thus, the studies of pre-purchase search behavior presented in Subsection 2.1 indicate that there is considerable heterogeneity of choice set sizes of consumers. Furthermore, the classification in thorough, balanced-thorough and non-thorough shoppers in Claxton et al. (1974) suggest a unimodal, skewed distribution of choice set sizes.

Formally, we model choice set size heterogeneity by applying the functional form of a gamma distribution to govern the number of passenger car versions in the choice set. The likelihood that n passenger car versions are evaluated is

\[ p(n; \alpha, \theta) = \frac{e^{-n/\theta}}{\theta^n \Gamma(\alpha)} \alpha^{n-1} \]

where \( \Gamma(x) \) is the gamma function, \( \alpha \) the shape parameter, and \( \theta \) the scale parameter. There is no a-priori reason to choose a specific distribution to model choice set size heterogeneity. We desired a family of distribution that is defined for positive integers, able to generate a rich variety of shapes, and that can be parsimoniously parameterized. We use the following two sets of assumptions for the values of \( \alpha \) and \( \theta \):

(i) \( \alpha = 4 \) and \( \theta = 6 \); this distribution is characterized by mean \( \mu = 24 \) and standard deviation \( \sigma = 12 \);
(ii) \( \alpha = 4.5 \) and \( \theta = 7 \); mean \( \mu = 31.5 \) and standard deviation \( \sigma = 14.8 \).

The second set of assumptions that results in a larger choice set is used in policy runs of incentive schemes that can be expected to have an additional non-monetary effect of drawing attention to the reasons behind the scheme and of presenting individuals opportunities to act (cf. Peters et al., 2008). The first set of assumptions is used in the reference run and in policy runs where no such effect is expected. Both sets of assumptions result in the desired unimodal, skewed distribution.

3.5. Choice set composition: retention rates

In addition to specifying the size of the choice set, we attempt to identify and implement constraints on the construction of the choice set. Like actual decision processes, actual constraints are hardly accessible to measurement. The operationalization of constraints in our microsimulation model is based on the notion of pre-decisional constraints (Punj and Brookes, 2002), product-related decisions made in advance in order to simplify the purchase decision. Additionally, we focus on replacement purchases and make use of the predictive power the replaced vehicle has for the new vehicle (Lane and Potter, 2007; Torrentine and Kurani, 2007).

Replacement purchases are treated as first-order Markov processes with respect to selected vehicle attributes (Massy et al., 1970); i.e., attributes of the purchased vehicle are dependent on the corresponding attributes of the replaced vehicle. Colombo and Morrison (1989) and Massy et al. (1970) used this concept to investigate brand switching and brand loyalty in the automobile industry. In addition, they distinguish consumers as either hard-core loyal buyers or potential switchers. We postulate an analog dichotomous segmentation of the car buyer population: consumers exhibiting constraints with respect to a specific attribute (such consumers retain the value of the attribute when replacing their car) and consumers exhibiting no such constraints (the value of the attribute is independent from the replaced car). We apply this to the attributes make, car size class, fuel type, and transmission type. Constraints on attributes such as price and engine size are conceivable, but classification of such continuous attributes into categories is not straightforward and therefore not pursued. As a further simplification, we focus exclusively on the diagonal of the Markov transition matrices; i.e., on transition probabilities of the form

\[ p_{i,n} = c_{i,n} + (1 - c_{i,n})p_{i,n} \]

where, \( c_{i,n} \) is the share of buyers constrained with regard to attribute \( n \); \( p_{i,n} \) is the probability that an unconstrained buyer repeatedly chooses value \( i \) of attribute \( n \). With the knowledge of \( p_{i,n} \) and \( p_{i,n} \), \( c_{i,n} \) can be calculated. In the presented microsimulation model, \( p_{i,n} \) is determined by the discrete choice model operationalizing the second, compensatory decision stage. The transition probabilities \( p_{i,n} \) are derived from a full-scale dataset of car transaction behavior in spring 2005 in Switzerland. The operationalization in the microsimulation model is as follows: the diagonals of the transition matrices for the attributes make, car size class, fuel type, and transmission type are imposed as boundary conditions in the reference run. The numbers of car buyers that are constrained are iteratively determined in order to satisfy these boundary conditions. The resulting distributions of constrained car buyers for all values of the considered attributes are a crucial input to the policy runs.

The following implicit assumptions underlie the above presented procedure: constraints are assumed to be homogeneously distributed over the sociodemographic groups. This assumption is sensible based on the results of Kiel and Layton (1981), Punj and Brookes (2002), and Punj and Staelin (1983), which indicate that demographic variables are of little value in distinguishing between segments of pre-decisional or decision behavior. Furthermore, the constraints with respect to different attributes are uncorrelated with each other. Finally, the occurrence of constraints does not influence choice set size. Although the occurrence of constraints is likely to affect choice set size (Johnson
and Russo, 1984), it is not immediately clear whether constraints will reduce or increase this parameter (Punj and Brookes, 2002). Based on the results of Punj and Brookes (2002), one can conclude that constraints with regard to car make can be expected to lead to smaller, more focused choice sets, and constraints with regard to car size class, fuel type, and transmission type result in larger, more heterogeneous choice sets. Thus, constraints not only influence the size of the choice set, but also its breadth. However, this empirical basis is not strong enough to operationalize choice set breadth and the resulting impact of constraints. Therefore, we retain the assumption that choice set size is independent from the occurrence of constraints.

3.6. Multi-attributive weighting

The multi-attributive weighting stage is operationalized by a discrete choice model, the traditional approach in modeling disaggregated vehicle type choice (see Choo and Mokhtarian (2004) and de Jong et al. (2004) for informative reviews). Discrete choice models forecast individual vehicle type choices based on the alternative’s technical and the decision-maker’s sociodemographic variables; these variables determine an alternative’s choice probability

\[ P_i = \frac{V_i}{\sum_{j \in I} \exp(V_j)} = \frac{\exp(\sum_{j \in I} \beta_j C_j)}{\sum_{j \in I} \exp(\sum_{j \in I} \beta_j C_j)} \]

\( P_i \) is the choice probability and \( V_i \) the utility of alternative \( i \); \( I \) is the decision-maker’s choice set, the C’s denote technical or sociodemographic variables, and the \( \beta \)’s the corresponding weighting factors. We desired to forecast choices on the aggregation level of a single passenger car version. A discrete choice model that meets this requirement is the multinomial logit model presented in COWI (2002). The parameters of this model were estimated for the 40 different sociodemographic groups presented in Subsection 3.2, based on a full-scale dataset of Danish households that purchased a vehicle in 1997. According to COWI (2002), this model is valid for cross-country policy analysis in European countries. The following eight parameters are utilized in order to quantify the choice probability of a specific passenger car version:

- logarithm of purchase price in € (\( C^1 \));
- fuel costs in € per 100 km (\( C^2 \));
- logarithm of length in millimeter (\( C^3 \));
- logarithm of luggage capacity in liter (\( C^4 \));
- logarithm of acceleration time from zero to hundred kilometer per hour in seconds (\( C^5 \));
- lower medium with respect to purchase price (dummy variable, \( C^6 \));
- upper medium with respect to purchase price (dummy variable, \( C^7 \));
- home market brand (dummy variable, \( C^8 \)), based on the classification of the synthetic Swiss population in German-speaking (affinity to German brands), French-speaking (affinity to French brands), and Italian-speaking households (affinity to Italian brands).

Multinomial logit models exhibit the independence of irrelevant alternatives property. Unfortunately, the documentation in COWI (2002) is not specific whether tests on violations of this property have been performed. Indications for the model’s validity are the following studies that present similar, disaggregated models: Choo and Mokhtarian (2004), de Jong (1996), and Mannering et al. (2002) estimated multinomial logit models of vehicle type choice and verified that the assumption of independence of irrelevant alternatives was fulfilled.

3.7. Perception of monetary values

To incorporate perception of monetary values according to Subsection 2.4, agents who do—and agents who do not—segregate the monetary value of an incentive scheme from the purchase price are distinguished. The utility of a specific passenger car version \( i \) is governed by the mathematical formulation

\[ V_i = \begin{cases} \beta^1 C^1_i + \beta^1 x' + \sum_{j=2}^{8} \beta^j C^j_i & \text{segregation, } x < 0; \\ \beta^1 C^1_i + \lambda \beta^1 x' + \sum_{j=2}^{8} \beta^j C^j_i & \text{segregation, } x > 0; \\ \beta^1 \ln(c^1_i + x) + \sum_{j=2}^{8} \beta^j C^j_i & \text{else}. \end{cases} \]

The \( \beta \)’s and the \( C \)’s are defined in Subsection 3.6, \( c^1 \) is the purchase price, \( x \) the monetary value of the incentive, \( \lambda \) ensures asymmetry between positive (fees) and negative (rebates) values of \( x \) (loss aversion); \( x' = bx \) is a linear transformation of the magnitude of \( x \), with \( b = 0.0001 \) the value of the natural logarithm’s first derivative at a value of 10,000. This transformation is motivated by the attempt to identify an appropriate elasticity for segregated values of financial incentives based on the logarithmic formulation of the purchase price in the discrete choice model (Subsection 3.6). The logarithmic curve yields unrealistic elasticities for small values; it is sensible to assume that the logarithmic formulation in the discrete choice model represents elasticities only in the range of values that correspond to purchase prices of new passenger cars. The reference point “zero” is therefore assumed to be at the lower bound of the range of car purchase prices (10,000€). Segregated monetary values of incentives are incorporated in a linear manner. Reasons of compatibility with the incorporation of the purchase price in the multinomial logit model would suggest using a logarithmic formulation; but, as already stated, the logarithmic function yields unrealistic elasticities for small values. In total, the above presented formulation has three free parameters: \( \lambda, b \), and the fraction of car buyers who segregate monetary values of incentives. We assume \( \lambda = 1.3 \) and the fraction of car buyers who segregate monetary values of incentives to be 75%.

4. Microsimulation results and validation

4.1. Reference run

In this section, we present results of the reference run for the year 2005 without additional policy scenarios. The microsimulation approach allows simulating a large and flexible number of agents with individual decision strategies. An appropriate number of agents is chosen in order to eliminate random effects caused by the stochastic nature of the agent’s decision processes. In each of the runs presented, 100,000 agents are simulated, leading to 100,000 simulated car purchases. We investigate the added value of the full-scale microsimulation incorporating gamma heterogeneity of choice set size and boundary conditions on switching behavior by comparing it to reduced model versions and market observations of 2005 (Subsection 4.2). In Subsection 4.3, we focus on comparing the full-scale microsimulation to market observations as a means of validating the microsimulation model. For this, the following forecasts and market observations are used:

- the aggregate measures diesel share, average curb weight, average CO2 emission and average engine capacity of the new
passenger car fleet, presented in Table 1, describe simulation performance on an aggregate level:
- the distribution of market shares over categories of CO₂ emission, curb weight and rated power, presented in Fig. 3, provide a more detailed picture of simulation performance;
- the microsimulation approach offers the ability to generate results on a much more detailed level. This potential is exploited in Fig. 4; market shares over categories of CO₂ emission, curb weight and rated power are presented over car size classes. This allows for a highly resolved assessment of simulation performance.

A common approach to evaluate the quality of microsimulation results is the use of a set of statistical performance metrics (de Haan and Rotach, 1998). We assess the generated distributions of N forecasted market shares by determining the following three performance metrics, presented in Table 2: normalized mean

### Table 1
Aggregated market observations compared to results of three reference runs with different assumptions for individual decision processes.

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<thead>
<tr>
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<tbody>
<tr>
<td>Share of diesel cars (%)</td>
<td>24.6</td>
<td>30.3</td>
<td>36.9</td>
</tr>
<tr>
<td>Average curb weight (kg)</td>
<td>1438</td>
<td>1550</td>
<td>1440</td>
</tr>
<tr>
<td>Average CO₂ emission (g/km)</td>
<td>190</td>
<td>207</td>
<td>178</td>
</tr>
<tr>
<td>Average engine capacity (ccm)</td>
<td>1958</td>
<td>2281</td>
<td>1889</td>
</tr>
</tbody>
</table>

Fig. 3. Results of reference runs (filled squares) with three different assumptions for individual choice processes (see Subsection 4.2) compared to market observations (unfilled circles).
absolute error $NMAE = \frac{1}{N} \sum_{i=1}^{N} |f_i - y_i| / \sum_{i=1}^{N} y_i$, mean fractional bias $MFB = 1/N \sum_{i=1}^{N} (f_i - y_i) / (\bar{f} + \bar{y})$, and correlation coefficient $COR = 1/N \sum_{i=1}^{N} (y_i - \bar{y})(f_i - \bar{f}) / (\sigma_y \sigma_f)$; $f_i$ are the forecasted values, $y_i$ are the actual market observations; $\bar{f}$ and $\bar{y}$ the respective averages, and $\sigma_f$ and $\sigma_y$ the respective standard deviations.

4.2. Comparison of different model versions

The above-mentioned results were generated for the following three distinct simulation runs with different assumptions for individual decision processes:

- **Random choice**: agents randomly choose a car from the universal choice set with uniform choice probability. Consequently, the results of this simulation run mirror all technical characteristics of the underlying universal choice set;
- **COWI (2002)**: this corresponds to the discrete choice model presented in COWI (2002); the attribute weights of the multinomial logit model remain the sole determinant of the choice probabilities;
- **Bounded choice**: the full-scale, bounded rational choice model incorporates gamma heterogeneity as presented in Subsection 3.4 and the boundary conditions on switching behavior as presented in Subsection 3.5.

Investigating both the generated aggregated measures and the detailed distributions of market shares in the case of the random choice model reveals the influence of the universal choice set on the forecasts. Therefore, these results are the baseline to which the other two simulation runs are compared. In general, the implementation of the choice model described in COWI (2002) leads to better simulation performance. For the results of the full-scale microsimulation, a further consistent improvement can be observed. The COWI (2002) model forecasts a diesel share that is too high, even exceeding the value forecasted by the random choice model. The bounded rational decision model leads to a much better forecast of this particular aggregate measure. Experimentation with the boundary conditions on switching behavior confirms the intuitive explanation that fuel type retention causes this effect. This is an important example where
Energy use and CO₂ emissions of passenger cars are determined by vehicle transaction behavior, vehicle type choice, and vehicle usage (de Haan et al., 2007). The presented microsimulation yields the demand for new passenger cars on the level of single passenger car versions, conditional on the acquisition of a vehicle. Vehicle usage of new passenger cars purchased can be determined based on expected usage across aggregate vehicle categories. Due to the focus on the cohort of new passenger cars purchased, a synthetic population of car purchasing households underlies the microsimulation.

A general feature of microsimulation models is their relative complexity (Brown and Harding, 2002). However, an advantage of such models is that they facilitate pseudo-experimentation of incentives (Halpin, 1999); i.e., the complexity of policy structures can be represented and detailed structural changes as an effect of such policies can be investigated. Microsimulation provides a framework in which the nature of a policy and the structural changes it causes can be explored, keeping in view desired or undesired effects. A further advantage of microsimulation models is that they provide a framework for integrating technical knowledge, empirical insights and theoretical results obtained on the fundamental decision-making units (Orcutt et al., 1961).

In Section 4, we presented results for the reference run without additional policy scenarios. These results were used to compare the full-scale microsimulation to reduced model versions and as a means for validation. The introduction of facets of bounded rationality, gamma heterogeneity of choice set size and the boundary conditions on switching behavior, resulted in consistent improvement of simulation performance (Subsection 4.2). The full-scale microsimulation is able to replicate market observations with very high accuracy.

We recommend the agent-based microsimulation as a tool to evaluate policies that influence individual purchase decisions of new passenger cars, taking into account the complexity and heterogeneity of individual decision units and the complex technological structure of the new passenger car market. The microsimulation is presented using Swiss data in order to construct the synthetic population and the universal choice set of all alternatives on offer. However, given the availability of this data, the presented model can be applied in EU countries without restrictions. The main limitation of the presented agent-based microsimulation is inherent to modeling: past observations of consumer behavior are used to forecast the behavioral response to a future policy instrument. Therefore, meaningful statements are restricted to a time-scale over which the characteristics and decision processes of individual decision-making units and the technological structure of the new passenger car market are stable. Our confidence in the model is bolstered on the one hand by the success with which market observations are forecasted. On the other hand, we expect that the implementation of empirical evidence with regard to the behavioral response of consumers enhances the models forecasting capability.

### 6. Conclusion and outlook

We presented an agent-based microsimulation model, featuring a highly resolved car fleet and differentiated consumer segments. The presented approach of agent-based microsimulation is useful as a tool to evaluate policies that influence

<table>
<thead>
<tr>
<th>Car Size Class</th>
<th>CO₂ (%)</th>
<th>MFB (%)</th>
<th>COR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random</td>
<td>62.00</td>
<td>16.16</td>
<td>0.672</td>
</tr>
<tr>
<td>COWI (2002)</td>
<td>59.71</td>
<td>−8.42</td>
<td>0.715</td>
</tr>
<tr>
<td>Bounded</td>
<td>48.73</td>
<td>−7.92</td>
<td>0.787</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Rated Power</th>
<th>CO₂ (%)</th>
<th>MFB (%)</th>
<th>COR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random</td>
<td>57.06</td>
<td>5.23</td>
<td>0.716</td>
</tr>
<tr>
<td>COWI (2002)</td>
<td>52.36</td>
<td>−16.36</td>
<td>0.811</td>
</tr>
<tr>
<td>Bounded</td>
<td>48.01</td>
<td>−14.57</td>
<td>0.841</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>CO₂ × Car Size Class</th>
<th>CO₂ (%)</th>
<th>MFB (%)</th>
<th>COR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random</td>
<td>63.66</td>
<td>17.77</td>
<td>0.691</td>
</tr>
<tr>
<td>COWI (2002)</td>
<td>60.46</td>
<td>−11.23</td>
<td>0.738</td>
</tr>
<tr>
<td>Bounded</td>
<td>51.55</td>
<td>−3.98</td>
<td>0.777</td>
</tr>
</tbody>
</table>

NMAE (normalized mean absolute error), MFB (mean fractional bias), and COR (correlation coefficient) for the distributions of market shares depicted in Fig. 3 (upper half of the table) and Fig. 4 (lower half of the table). The values for a perfect model are: NMAE and MFB = 0; COR = 1.

### 4.3. Model validation

With respect to the forecasted aggregate measures listed in Table 1 and the generated distribution of market shares over categories of CO₂ emission, curb weight and rated power depicted in Fig. 3, the full-scale microsimulation is able to reproduce market observations with very high accuracy. The highly resolved results presented in Fig. 4 show that the microsimulation model is valid on a very detailed level. Furthermore, the microsimulation approach allows excluding the possibility that two counteracting model errors compensate each other on an aggregate level; such effects would have become visible during the analysis of the highly resolved model results. The results presented in Fig. 4 allow the identification of model errors that still exist and to further enhance the performance by calibrating the model. This is accomplished and discussed in de Haan et al. (2009).

### 5. Discussion

The goal of our research was to proceed with the line of argument presented in Peters et al. (2008) and construct a microsimulation model of car choice behavior featuring a highly resolved car fleet and differentiated consumer segments. Additionally, we elaborated on the importance of individual decision processes and developed a conceptual two-stage model of the decision process based on the notion of bounded rationality. This conceptual model served as a template for operationalizing individual decisions in the resulting agent-based microsimulation model.

<table>
<thead>
<tr>
<th>Car Size Class</th>
<th>CO₂ (%)</th>
<th>MFB (%)</th>
<th>COR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random</td>
<td>28.97</td>
<td>29.43</td>
<td>0.759</td>
</tr>
<tr>
<td>COWI (2002)</td>
<td>22.83</td>
<td>20.07</td>
<td>0.846</td>
</tr>
<tr>
<td>Bounded</td>
<td>18.68</td>
<td>18.06</td>
<td>0.863</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Rated Power</th>
<th>CO₂ (%)</th>
<th>MFB (%)</th>
<th>COR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random</td>
<td>34.86</td>
<td>−9.94</td>
<td>0.560</td>
</tr>
<tr>
<td>COWI (2002)</td>
<td>17.40</td>
<td>3.25</td>
<td>0.726</td>
</tr>
<tr>
<td>Bounded</td>
<td>16.51</td>
<td>−1.29</td>
<td>0.777</td>
</tr>
</tbody>
</table>

Table 2

Calculated performance metrics.

<table>
<thead>
<tr>
<th>Car Size Class</th>
<th>CO₂ (%)</th>
<th>MFB (%)</th>
<th>COR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rated Power</td>
<td>30.63</td>
<td>12.17</td>
<td>0.713</td>
</tr>
<tr>
<td>COWI (2002)</td>
<td>15.63</td>
<td>−2.68</td>
<td>0.821</td>
</tr>
<tr>
<td>Bounded</td>
<td>15.24</td>
<td>−1.06</td>
<td>0.827</td>
</tr>
</tbody>
</table>

The limited awareness of alternatives by consumers outlined in Subsection 2.3 has the potential to cause inertia in the behavioral response to incentive schemes.
individual purchase decisions of new passenger cars due to the following reasons:

- it can account for the heterogeneity of individual decision units;
- the complex technological structure of the new passenger car market can be represented;
- it facilitates a detailed investigation of complex policy structures and structural changes as an effect of such policies;
- the focus on the fundamental decision-making units offers a natural framework for incorporating bounded rational decision processes.

The microsimulation model was constructed using Swiss data, but given data availability, it can be applied in European countries. Ultimately, the microsimulation approach predestines the integration of the presented model with other microsimulation models, e.g., large-scale multi-agent simulations of travel behavior and traffic flow (Barrett et al., 1995; Raney et al., 2003).

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COWI, 2002. Fiscal measures to reduce CO₂ emissions from new passenger cars. COWI Environmental consultants, final report under a contract to European Commission, DG Environment.


