Dissertation

Planning the market introduction of new products: An agent-based simulation of innovation diffusion

Verfasser

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Contents

List of Tables

List of Figures

List of Algorithms

Abbreviations and Acronyms

ABM .... Agent-based model
ABMS .... Agent-based modeling and simulation
ABS .... Agent-based simulation
ABSS .... Agent-based social simulation
BtL .... Biomass to liquid
CERN .... Organisation Européenne pour la Recherche Nucléaire
CHP .... Co-heating and power
CODA .... Continuous opinions, discrete actions
EU .... European Union
FT .... Fischer-Tropsch
GHG .... Greenhouse gas
SEIR .... Susceptible, exposed, infected, removed/recovered
SIR .... Susceptible, Infectious, Recovered/Removed
SUV .... Sport utility vehicle
TPB .... Theory of planned behavior
w.r.t. .... with respect to
WoM .... Word-of-mouth
XML .... Extensible Markup Language
XSD .... XML Schema

Nomenclature

Model Entities

A .... Set of attributes
A_j .... Attribute j
C .... Set of consumer agents
C_k .... Consumer k
P .... Set of products
P_i .... Product i
S .... Set of points of sale
S_l .... Point of sale l

Indices and Cardinalities

i .... Product index
j .... Attribute index
k .... Consumer index
l .... Point of sale index
m .... Number of products
n .... Number of attributes
r .... Advertising event index

Parameters

$\alpha_k^{posSelect}$ .... spatial exponent that weights distance in point of sale selection
$\alpha^{spatial}$ .... Clustering exponent (spatial graph model)
$\beta^{spatial}$ .... Geodesic exponent (spatial graph model)
β^{watts} .... Rewiring probability in Watts and Strogatz (1998) small-world network model
ϵ^{prod} .... Product utility evaluation error range
λ .... Information decay exponent
ε^{pos} .... Point of sale selection error range
$\varepsilon^{productUtil}$ ...... Product utility random error range ($\epsilon^{productUtil} \sim (-\varepsilon^{productUtil}, +\varepsilon^{productUtil})$)

Parameters

a_k .... Attraction parameter of point of sale k

c_k .... Connectivity of vertex k

G .... Social network graph

k^{watts} .... Initial number of edges per node in Watts and Strogatz (1998) small-world network model

k_l .... Attraction parameter for point of sale l

L_k^{cons} .... Consumer k's home location defined as a point (ρ_k, λ_k) in a geographical coordinate system

L_l^{pos} .... Point of sale l's s location defined as a point (ρ_l, λ_l) in a geographical coordinate system

$n_{connect}^{barabasi}$ .... Number of edges added per vertex in Barabási and Albert (1999) network model

$n_{init}^{barabasi}$ .... Number of initial vertices in Barabási and Albert (1999) network model

n^{bins} .... Number of bins in histograms used to store product attribute information

$n^{consumers}$ ...... Number of consumers

$n_k^{posHist}$ .... Point of sale history size

n_r^{reach} .... Number of agents exposed to mass advertising event r

o_j .... Attribute j's observability

$p^{comm}(\Delta u_{i,j,k})$ .. Function that assigns a probability of WoM communication to a given change in attribute utility valuation

$P_r^{impactAware}$ .... Probability that advertising event r has an impact on an exposed agent that is already aware of the advertised product

p^{link} .... Link probability in Gilbert (1959) random graph model

$P_r^{makeAware}$ ..... Probability that an agent exposed to advertising activity r becomes aware of the advertised product

$p_k^{recentPOS}$ ...... Probability of selecting a recently visited point of sale

$p_{i,l,t}$ .... Price of product P_i at point of sale l at time t

S_r^{adv} .... Set of points of sale at which POS advertising activity r is active

$s_{i,l,t}$ .... Availability of product P_i at point of sale l at time t

T_r^{adv} .... Set of communicated attribute values in advertising activity r

t_r^{from} .... Start time of point of sale advertising activity r

t_r^{till} .... End time of point of sale advertising activity r

t_r .... Time of mass advertising event r

V .... Product valuation matrix

v_j^{max} .... Maximum value of attribute A_j

v_j^{min} .... Minimum value of attribute A_j

$v_{i,j}^{true}$ .... Product i's true attribute value for attribute j

W .... Social network weighted adjacency matrix
w_r^{adv} .... Weighting factor that determines the impact of advertising activity r
w^{ad} .... Advertising impact factor
$w_{a,b}$ .... Influence weight of consumer C_a on C_b in the social network
$X(\omega)$ .... Real-valued, continuous random variable equidistributed on $[0,1]$ (used for drawing random values in various algorithms)
$Y_{a,b}$ .... Interarrival time distribution of communication events at the edge that connects consumer agents C_a and C_b

Functions

$\ell(a,b)$ .... Geodesic distance between agents a and b (distance between consumer agents or consumer agent and point of sale)
$G_k(t)$ .... Interpurchase time distribution function of consumer k
$u_{j,k}(v_{i,j,k}^{estimate})$ ... Consumer agent C_k's utility function for attribute j

Variables

$\Delta_{(a,b)}u_{i,j,k}$ ...... Change in agent C_a's attribute utility estimate since the last time it communicated with agent C_b
ϵ^{pos} .... Point of sale selection error
$\epsilon^{productUtil}$ ...... Product utility error variable
ε^{prod} .... Product utility evaluation error variable
$a_{j,k}^{attr}$ .... Consumer k's awareness of attribute j
$a_{i,k}^{prod}$ .... Consumer k's awareness of product i
c_i .... Degree of vertex i
E .... A consumer's evoked set during the purchasing process
g .... Histogram bin index
$hist_{i,j,k,g}$ .... Consumer agent C_k's histogram bin g for attribute j of product i
I_k .... Interpurchase time of consumer k (random variable with distribution function $G_k(t)$)
S_k^{hist} .... Point of sale history queue of consumer agent k
T .... List of topics in a consumer communication event
t .... Simulation time (continuous)
u_l^{hist} .... Utility obtained at the last purchase at point of sale S_l
$u_{i,j,k}$ .... Consumer k's partial utility of product P_i's attribute j
$u_{i,k}$ .... Consumer C_k's utility valuation of product i

$v_{i,j,k}^{estimate}$ .... Consumer agent C_k's estimate of product P_i's attribute value for A_j

1. Introduction

In today's business environment, firms' ability to create and maintain competitive advantage and secure sustainable assets is critically dependent upon their ability to successfully market innovations. Quantitative models of innovation diffusion (i.e., the spread of new ideas, products, and practices throughout a society over time, cf. Rogers, 1962) have therefore attracted strong interest both from management scholars and from practitioners that are responsible for new product marketing decisions.

Pioneering efforts to mathematically describe the diffusion of innovations were made in the 1960s by Fourt and Woodlock (1960), Mansfield (1961), and Bass (1969). The model developed by Bass (1969), which characterizes the diffusion of an innovation as a contagious process that is initiated by mass communication and propelled by word-of-mouth, has been particularly influential and has spawned a large body of literature that encompasses various model extensions, estimation and calibration methods, parameter estimates for specific industries, and numerous applications[1]. The aim of these models is to provide empirical generalizations of prototypical diffusion patterns at the aggregate (i.e., market) level in order to estimate the likely diffusion of a new product through extrapolation from early sales. To provide stable estimates, these aggregate models typically require considerable amounts of data covering most of the product's lifespan, including takeoff prior to growth and slowdown prior to maturity (Srinivasan and Mason, 1986; Chandrasekaran and Tellis, 2007). Parameter estimation for these models is therefore primarily of historic interest because by the time sufficient observations are available, it is usually too late to use the estimates for forecasting purposes (Mahajan et al., 1990). Furthermore, most decision-makers are less interested in immutable and precise (but possibly wrong) forecasts, but rather in evaluating likely effects of the decision variables at their disposal, for which aggregate models provide only limited support. In particular, managers responsible for new product marketing decisions may benefit significantly from information on how the marketing mix factors product, price, promotion, and distribution affect the spread of an innovation.

The main objective of this thesis is to introduce an innovation diffusion model that supports decision-makers in the process of planning the market introduction of new products by simulating the impact of various strategic choices on the diffusion process. To overcome inherent

[1] For reviews of the extensive literature, cf. Chatterjee and Eliashberg (1990); Mahajan and Muller (1979); Mahajan et al. (1990, 1995, 2000); Sultan et al. (1990); Parker (1994); Meade and Islam (2006).

limitations of phenomenological aggregate-level models, we apply agent-based modeling and simulation, a methodology that has increasingly been adopted in the social sciences in recent years (cf. Squazzoni, 2010). As the agent-based approach is not limited in its capacity to account for individual heterogeneity and social structure, it opens up new research opportunities. Rather than describing macro-scale dynamics directly, agent-based models capture emergent phenomena that arise from individuals' micro-level interactions. This bottom-up approach can easily incorporate micro-level drivers of adoption, bounded rationality, and imperfect information as well as individuals' heterogeneity in terms of attributes, preferences, behavior, and linkages in the social network.

In the spirit of modern complexity science, these models have the potential to reproduce and explain complex non-linear diffusion patterns observed in real world as the result of relatively simple local micro-level interactions. Agent-based approaches modeling innovation diffusion are still in their infancy, but they promise to create intriguing new research opportunities by facilitating a transition from an aggregate-level to an individual-level perspective.

1.1. Aims and objectives

Existing agent-based innovation diffusion research can be divided into two major streams: (i) highly stylized modeling aimed at general theoretical insights, and (ii) highly specific models tailored to particular practical applications.

The first stream is based on abstract, generic representations of diffusion processes and uses agent-based models as tools for theoretical inquiry. These models are typically based on simple, if not simplistic, conceptions of human decision making and do not aim to provide forecasts or support managerial decision-making. The quantitative results they produce should therefore only be interpreted qualitatively with respect to the modeled effects.

The latter models are concerned with practical applications and aim to provide forecasts and policy analyses. They provide managerial guidance and policy analyses, but they are usually not sufficiently generic to be used in any other context than the substantive domains modeled.

This thesis aims at the gap between these two streams of research, which is a challenging but promising area both from a scientific and a managerial perspective. In particular, the main aim is to provide managers with a versatile, adaptive, robust, and easy to control model that incorporates sufficient detail and is as complete as possible while still being applicable to a range of applications as wide as possible. In order to achieve this aim, the dissertation intends to accomplish the following key objectives:

Objective 1: Identify advantages and limitations of an agent-based modeling approach in the context of innovation diffusion research.

Objective 2: Thoroughly review and discuss the available literature on innovation diffusion modeling in order to highlight potential areas for research, inform the methodology used for this research, and to guide the model development process.

Objective 3: Design and implement an agent-based model of innovation diffusion that allows decision-makers to evaluate product launch strategies in a competitive setting.

Objective 4: Demonstrate the capability of the model to tackle real-world problems by means of an empirically grounded application case.

1.2. Research contributions

The thesis contributes to the diffusion modeling literature by addressing a number of key aspects that have been largely neglected in quantitative diffusion research so far, despite their particular relevance in diffusion processes and agent-based modeling's excellent ability to tackle them.

First, the proposed model is spatially explicit and provides decision makers with the opportunity to evaluate roll out strategies geographically. While innovation diffusion has long been recognized as a spatial process (cf., e.g., Hägerstrand, 1967), scant attention has been paid to this aspect in agent-based diffusion models so far.

Second, the model incorporates repeat purchase decisions and consumers' post purchase evaluations and covers all stages of the innovation-decision process (cf. Rogers, 1962), including implementation and confirmation. Although diffusion models are by definition primarily concerned with initial adoption, repeat purchase plays an important role in the diffusion of many products, e.g., as a social signal. Furthermore, it is a major source of revenue in many industries. The agent-based model proposed in this thesis may improve our understanding of the interaction of initial adoption and repeat purchases which jointly shape diffusion processes of non-durable products. Repeat purchases should not be neglected for practical reasons, since they typically determine a firms' long-term growth and profitability. Developing models for sales rather than for adoption is therefore a promising area of research (cf. Peres et al., 2010; Delre et al., 2010).

Third, the model incorporates competition by simulating sales of multiple products characterized by multiple attributes and thereby enables decision-makers to conduct product- and brand-level analyses. Models proposed in the literature so far are typically based on the assumption that the innovation has its own exclusive market potential, which is not affected by competitors' actions. More often than not, however, firms face intense competition from incumbents and other innovators when introducing new products. Tools for analyzing innovation diffusion in a competitive setting are therefore of great theoretical as well as practical relevance.

The agent-based approach offers excellent opportunities to develop a versatile model that is generalizable and still applicable to specific cases. Furthermore, it allows us to pursue cutting-edge research interests identified by Peres et al. (2010) in a recent review, including spatial diffusion, brand-level rather than industry-level analysis, and a shift from forecasting to managerial diagnostics. In particular, this thesis contributes to the innovation diffusion literature by

- modeling all stages of the innovation-decision process,
- modeling sales rather than exclusively focusing on initial adoption,
- modeling the competitive diffusion of multiple products,
- complementing the temporal focus with the spatial dimension,
- incorporating a spatially explicit social network model, and
- incorporating multi-attribute consumer decision-making.

By explicitly considering these aspects, the developed model enables decision-makers to evaluate the impact of key marketing variables on the diffusion process, including (i) product characteristics (i.e., the choice of product attributes), (ii) rollout strategies (i.e., the temporally and spatially explicit choice of points of sale), (iii) pricing strategies, and (iv) advertising strategies.

The capability of the model to tackle real world problems is illustrated by means of a particularly interesting, empirically grounded application case on the diffusion of a second generation biofuel at the Austrian market. Simulation scenarios illustrate how the model can be used to estimate the market potential of a second generation biofuel and evaluate product launch strategies under supply constraints. For this sample application, a spatially explicit model is of particular value since biofuel production capacity will be limited, which makes it necessary to choose the (initial) points of sale (i.e., gas stations) while taking into account both rich sources of biomass and the geographic concentration of consumers. The sample application also benefits from the explicit modeling of consumer behavior in a multi-brand setting, realistically captures market dynamics, and obtains insights into their effects. It thereby illustrates how agent-based models may provide managers with valuable decision support in the process of developing product launch strategies in a competitive setting.

1.3. Organization of the thesis

Chapter 1.3 starts with a brief general introduction to innovation diffusion and then contrasts various aggregate and disaggregate modeling techniques that have been used to study innovation diffusion. The chapter aims to provide a broad methodological overview and discusses the available modeling approaches critically by highlighting their respective advantages and limitations. Finally, the chapter introduces agent-based modeling, a bottom-up modeling approach that recognizes the social nature of the diffusion of innovations phenomenon and promises to overcome several inherent limitations of other approaches. It thereby motivates the use of an agent-based approach in the research presented in this thesis.

Chapter 3 provides a general introduction on agent-based modeling in the social sciences and then extends the literature review by examining agent-based diffusion modeling techniques as well as models that have been published in the peer-reviewed literature to date. In particular, the chapter discusses available approaches to model consumer adoption behavior and social influence in agent-based diffusion models. It then proceeds to outline theoretical findings that have been contributed to innovation diffusion research through agent-based modeling and closes with a systematic review of the growing number of real-world applications.

Based on the extensive literature review in the first two chapters and the research gaps identified, Chapter 4 starts by defining modeling objectives that guide the model development process, proceeds to discuss the chosen strategy for modeling time and space, and then provides the formal model design. In particular, the chapter outlines how the individual elements of the model — producers, products, points of sale, consumers and the social network formed by them — are formalized and specifies the mechanisms that drive the behavior of the simulation.

Building upon the theoretical model design, Chapter 5 covers the implementation and testing of the agent-based diffusion model developed in this thesis. First, it briefly reviews available software tools for implementing agent-based models and then provides details on the platform and tools chosen to implement the model in a computer simulation. The chapter closes with a description of the program architecture of the simulation tool and a description of the mechanism used to parameterize the model for the simulation of specific scenarios.

To evaluate the developed model and illustrate its potential for tackling real-world problems, as well as to provide insight into a particularly relevant application, Chapter 6 documents the use of the model to simulate the diffusion of a second generation biofuel on the Austrian market. The chapter first provides the background on first and second generation biofuels as well as the specific application case biofuel that is currently under development. It then introduces the sources and collection techniques used to obtain the data required to parameterize the model. Following this, the chapter outlines the experimental design and presents results for various simulated scenarios that provide interesting insights into the market potential of the innovation.

Finally, Chapter 7 concludes the dissertation by summarizing results, highlighting key contributions, and providing various directions to fruitful avenues for future work.

2. Modeling the Diffusion of Innovations*

Innovation diffusion research seeks to understand how new ideas, products and practices spread throughout a society over time (Rogers, 1962). It is an interdisciplinary field with roots in anthropology (Wissler, 1915), sociology (Tarde, 1903), geography (Hägerstrand, 1967), political science (Walker, 1969), economics (Griliches, 1957), and marketing (Arndt, 1967) that has produced an impressive stream of literature over the past 50 years. Judging by the wealth of research, it is one of the most active areas in the social sciences (Rogers, 2003), which is not surprising given that innovation diffusion can be considered one of the major mechanisms of social and technological change (Katz et al., 1963).

The term "diffusion" embraces a number of key concepts including contagion, mimicry, and social learning (Strang and Soule, 1998). In particular, the diffusion of innovation paradigm postulates that markets are in fact dominated by social influences, i.e., individual decisions depend on what other consumers do (Delre et al., 2007a). The basic premise, which is confirmed by empirical research, is that new products, ideas and practices spread largely via interpersonal communication (Hägerstrand, 1967; Katz et al., 1963; Ryan and Gross, 1943; Rogers, 1983; Valente and Rogers, 1995; Valente and Davis, 1999; Valente, 2005). Empirical groundwork for this paradigm was laid by Ryan and Gross (1943), who found that social contacts, social interaction, and interpersonal communication were important influences on the adoption of new behaviors (Valente and Rogers, 1995). From an economic perspective, the theory of innovation diffusion is in line with Schumpeter's recognition that *"innovation... does not lend itself to description in terms of a theory of equilibrium"* (Schumpeter, 1928, p. 64), but must rather be understood as a dynamic process.

The innovation diffusion theory as introduced by Rogers (1962) is the most frequently cited publication in this field (Janssen and Jager, 2002). It also provides a comprehensive review of the scope and diversity of innovation diffusion research. Rogers (2003, p. 171–191) conceptualizes consumer adoption as a process and postulates that individuals progress through a sequence

* Parts of this chapter will also appear in the following joint publication (the author of this thesis is also the lead author of that paper):

> Kiesling E., Stummer C., Günther M., Wakolbinger L.M. (2011),
> Agent-based simulation of innovation diffusion: A review,
> *Central European Journal of Operations Research*, forthcoming.
> DOI 10.1007/s10100-011-0210-y

of five steps that determine whether they adopt or reject an innovation (i.e., the "innovation-decision process"):

(i) a knowledge stage, in which an individual has been exposed to an innovation and become aware of its existence, but does not actively seek more information,
(ii) a persuasion stage, in which an individual does actively seek information,
(iii) a decision stage, where the individual decides whether to adopt or to reject the innovation,
(iv) an implementation stage, in which the individual employs the innovation and determines its usefulness, and
(v) a confirmation stage, in which the individual finalizes the decision to adopt or reject the innovation based on experiences made during implementation.

Rather than assuming that individuals evaluate innovations "objectively" on their own at a specific point in time and make a rational decision accordingly, the theory highlights the importance of the dynamic formation of attitudes and subjective perceptions that are transmitted through communication among the members of the social system.

Rogers also suggests that the cumulative number of individuals that have adopted an innovation (i.e., purchased a new product at least once) typically follows an S-shaped curve and links this empirically supported finding to a classification of adopters into the following five categories based on their "innovativeness", which he defines as *"the degree to which an individual or other unit of adoption is relatively earlier in adopting new ideas than other members of a social system"* (Rogers, 2003, pp. 280): (i) innovators, (ii) early adopters, (iii) early majority, (iv) late majority, and (v) laggards. In the proposed conceptual model, the S-curve starts to rise slowly as soon as the first innovators adopt the innovation. Following that, the speed of diffusion increases due to early adopters. The curve is at its steepest when the early majority and late majority successively adopt the innovation before diffusion levels off as remaining laggards adopt the innovation only slowly.

While the model proposed by Rogers provides a rich conceptual framework and has been widely influential in innovation diffusion research, it does not provide researchers and managers with quantitative tools to study the diffusion of a new product or investigate the effect of strategic variables on the diffusion process. A number of approaches to capture innovation diffusion processes mathematically have therefore been developed since the early 1960s. The remainder of this chapter provides an overview of these quantitative models, which can be divided into aggregate and disaggregate approaches.

2.1. Aggregate models of innovation diffusion

Driven by managers' interest in forecasting sales of new products, the marketing tradition of diffusion modeling has come on strong since the early 1960s. Early efforts to describe the spread of new products in a marketplace mathematically were rooted in analogies in the models of epidemics, biology, and ecology (Mahajan and Muller, 1979). These seminal models described the diffusion of innovations by means of simple mathematical formulations which gradually became more sophisticated as the field developed. Because the formulations describe the relationships between variables on the macro-scale of analysis, the resulting models are also frequently referred to as macro-level models.

Aggregate models are typically based on a mathematical description of flows between mutually exclusive and collectively exhaustive subgroups in a population, such as adopters and nonadopters. "Traditional" aggregate models covered in the following section specify these flows by means of equations (typically differential equations). They constitute the vast majority of the diffusion modeling literature to date. System dynamics, a different aggregate modeling approach that conceptualizes innovation diffusion as a dynamic process in a complex system, will be covered in Subsection 2.1.2.

2.1.1. Parsimonious empirical models

In this section, we outline the "traditional" aggregate modeling approach, which has emerged from seminal contributions by Fourt and Woodlock (1960), Mansfield (1961) and Bass (1969). This approach is based on parsimonious mathematical models whose parameters are estimated statistically to most closely reproduce an empirically observed diffusion time series.

The rich stream of literature on these models has been reviewed by numerous authors. Mahajan and Muller (1979) review early contributions, Mahajan et al. (1990, 1995, 2000) provide an overview of the Bass model, its extensions and applications, Sultan et al. (1990) meta-analyze 213 estimates of innovation and imitation parameters of the Bass model, and Parker (1994) reviews theoretical origins, specifications, data requirements, estimation procedures and prelaunch calibration possibilities. More recently, Meade and Islam (2006) review the wealth of literature from a forecasting perspective and conclude that few research questions have been finally resolved.

Although diffusion modeling has become a vibrant research tradition, most reported work has consisted of refinements and extensions of the Bass diffusion model without alteration of its basic premise (Mahajan et al., 1990; Bemmaor, 1994). Most models therefore still show the structure of the basic epidemic model introduced by Bass, which comprises and includes as special cases the earlier models by Fourt and Woodlock (1960) and Mansfield (1961). In the following section, we therefore outline the Bass model as a salient example of a parsimonious empirical diffusion model that is widely cited and was selected as one of ten most influential papers in the first 50 years of Management Science (Hopp, 2004).

2.1.1.1. The Bass model

The Bass model conceptualizes the diffusion of consumer durables as a contagious process that is initiated by mass communication and propelled by word-of-mouth and describes this process by means of a differential equation for which a closed form solution exists (Bass, 1969). In particular, Bass follows Rogers' (1962) diffusion of innovations theory and specifies that the diffusion of an innovation is driven by two influences: (i) an external influence (e.g., advertising, mass media) and (ii) an internal influence (e.g., word-of-mouth) Note that Bass originally termed the parameters that control these influences "coefficient of innovation" and "coefficient of imitation", respectively, which suggests a dichotomous population that consists of innovators and imitators. Because the mathematical form of the model requires the assumption that the potential adopter population is homogeneous, however, Lekvall and Wahlbin (1973) proposed the now more commonly used terms "external" and "internal" influence, which we also use in the following.

According to the Bass model, an individual's probability of adopting a new product at time t, given she/he has not adopted yet, depends linearly on two influences: one which is not related to previous adopters and is represented by the parameter of external influence denoted as p, and one that is related to the number of previous adopters, represented by the parameter of internal influence denoted as q. The limiting probability that an actor who has not adopted yet at time t does so at time $t + \delta t(\delta t \to 0)$ is described by the hazard model

$$\frac{f(t)}{1 - F(t)} = p + qF(t), \tag{2.1}$$

where $f(t)$ is the probability of adoption at time t, $F(t)$ is the cumulative distribution function of adoptions at time t, and p as well as q are parameters.

Aggregate models are primarily concerned with modeling $n(t)$, the flow of consumers from the potential market M to the current market (Mahajan and Muller, 1979). Equation 2.1 is therefore typically used in the following reexpressed form:

$$n(t) = [p + q(N(t)/M)][M - N(t)], \tag{2.2}$$

where $N(t)$ is the number of consumers having adopted by time t. Plotting $n(t)$ over time yields a (skewed) bell-curve of new adoptions, whereas plotting $N(t)$ yields the typical S-shaped diffusion curve.

Figure 2.1 illustrates the conceptual structure of the Bass model. During the initial phase of the process, the diffusion is entirely driven by adoptions due to external influence (originally termed "innovators" by Bass). In the later stages of the process, the share of adoptions due to external influences diminishes gradually and is exceeded by the number of adoptions due to internal influence (originally termed "imitators") as diffusion "takes off" and the process becomes self-sustaining.

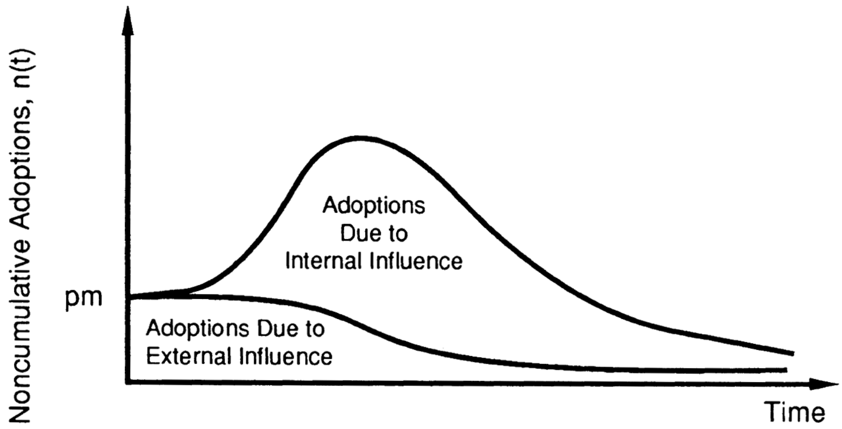


Figure 2.1.: Adoptions due to external and internal influence in the Bass model (Source: Mahajan et al., 1990).

Figure 2.2 illustrates typical diffusion curves for various values of the parameters p and q. The third parameter, number of potential adopters M, is usually assumed as constant, although extensions of the model with dynamic market potential have been developed (e.g., Mahajan et al., 1979). Sultan et al. (1990), based on an analysis of parameter estimates of 213 published applications of the Bass model, report that the average value of $p = 0.03$ and the average value of $q = 0.38$.

2.1.1.2. Extensions of the Bass Model

To incorporate additional aspects and reflect the complexity of new product growth, the original formulation of the Bass model has been extended widely since its introduction to marketing. Aspects considered in extended models include repeat purchasing (e.g., Dodson and Muller, 1978), dynamic market potentials (e.g., Mahajan et al., 1979), uncertainty about the value of the innovation (e.g., Kalish, 1985), negative word-of-mouth (e.g., Mahajan et al., 1984), word-of-mouth that systematically varies over time (Easingwood et al., 1983), and substitutes, complements and successive product generations (e.g., Norton and Bass, 1987).

Marketing decision variables such as price, advertising, distribution and supply restrictions have been incorporated as well, as we will discuss in the paragraph on prescriptive guidance in Subsubsection 2.1.1.4. For a more exhaustive survey of the aggregate diffusion modeling literature including extensions of the Bass model, we refer to Mahajan and Muller (1979); Mahajan et al. (1990); Parker (1994); Mahajan et al. (1995, 2000); Meade and Islam (2006).

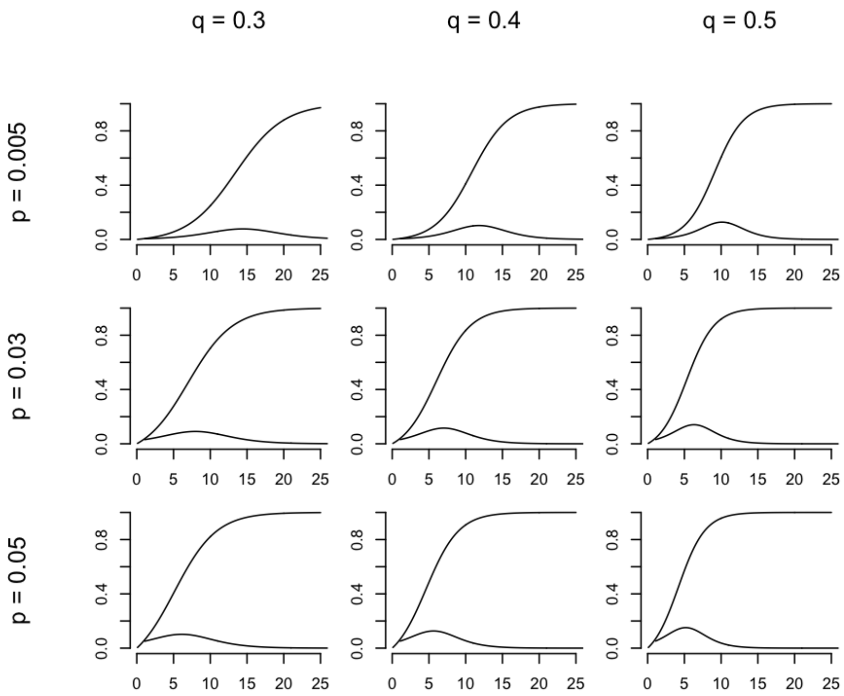


Figure 2.2.: Bass model adoption curves $N(t)$ and $n(t)$ for $m = 1$ and various values of p and q.

2.1.1.3. Strengths

One of the advantages of the aggregate modeling paradigm is that it provides a parsimonious and analytically tractable way to look at the whole market and interpret its behavior. A related advantage is that these models make use of market level data to forecast sales, which is typically more readily available than individual-level data. Assuming that sufficient data points are available, the model can be fitted to early sales data to obtain parameter estimates for new products. For the Bass model, the well-researched estimation literature provides a number of mature estimation methods, including ordinary least squares (Bass, 1969), maximum likelihood (Schmittlein and Mahajan, 1982), nonlinear least squares (Srinivasan and Mason, 1986) and genetic algorithms (Venkatesan et al., 2004). The Bass model fits many historic data on completed diffusion processes well (cf. Sultan et al., 1990) and is excellent at backcasting.

2.1.1.4. Limitations

Several limitations of aggregate-level models in general, and the Bass model in particular, have been identified in the literature.

Predictive power Although the Bass model has been widely adopted and employed for forecasting purposes in several companies after it was first proposed (Bass, 1980) and is still widely used in industry today (Thiriot and Kant, 2008), a number of authors have raised concerns over the reliability of parameter estimates (cf., e.g., Van den Bulte and Lilien, 1997) and, more generally, over the use of the Bass model for forecasting purposes (e.g. Bernhardt and Mackenzie, 1972; Heeler and Hustad, 1980; Kohli et al., 1999). Mahajan et al. (1990, p. 9) note that *"parameter estimation for diffusion models is primarily of historic interest; by the time sufficient observations have developed for reliable estimation, it is too late to use the estimates for forecasting purposes"*. Because the models need data at both turning points (takeoff prior to growth and slowdown prior to maturity) to provide stable estimates (Srinivasan and Mason, 1986; Chandrasekaran and Tellis, 2007), there is little use for them before or around takeoff (Kohli et al., 1999; Mahajan et al., 1990; Goldenberg et al., 2000), which is the time these forecasts are most valuable. In other words, traditional diffusion models require as input information about the events (takeoff and slowdown) that managers would like to predict (Chandrasekaran and Tellis, 2007).

Explanatory power Parsimonious aggregate models are not behaviorally based (Goldenberg et al., 2000), but their formulation is governed by the need for mathematical solvability, which may lead to unrealistic assumptions (Maier, 1998). It is therefore not surprising that these models do not reproduce the complexity of real-world diffusion patterns. Innovation failures, oscillations, and collapses of initially successful diffusions are phenomena observed in reality, but not explained by aggregate diffusion models (Strang and Macy, 2001; Maienhofer and Finholt, 2002).

Also, while the two coefficients of Bass-type models have appealing interpretations (internal and external influence, respectively), it is not clear whether they truly reflect the underlying diffusion mechanisms. Hohnisch et al. (2008) therefore refer to these models as "phenomenological" and thus emphasize that they provide empirical generalizations and do not aim to explain the mechanisms that cause diffusion processes. This can be linked to a more general widespread neglect of process in the social sciences, as criticized by Chattoe, who notes that *"collection of aggregate time series data does little to explain social change even when statistical regularities can be established"* (Chattoe, 2002, p. 114).

Limited potential to consider population heterogeneity The mathematical form of the Bass model requires the assumption that the potential adopter population is homogeneous (Tanny and Derzko, 1988; Chatterjee and Eliashberg, 1990; Bemmaor, 1994; Van den Bulte and Stremersch, 2004), which may be considered a gross simplification since potential adopters are typically heterogeneous in economic factors such as income, in their individual preferences, the information they have etc., and consequently in their propensity to adopt. The heterogeneous population argument was already used by Rogers (1962), who defined five adopter categories based on propensity to adopt. For a discussion of the debate between two alternative explanations for diffusion processes, viz. individual heterogeneity on the one hand, and awareness and information spreading mechanisms on the other hand, we refer to Bemmaor (1994).

To consider heterogeneity in traditional diffusion models, compartmental approaches that aggregate the population into a relatively small number of states such as unaware, aware, in the market, adopters etc. have been developed (e.g., Urban et al., 1990). However, compartment models still assume homogeneity and perfect mixing within compartments and do not consider heterogeneity in individual attributes and in the network structure of interactions (Rahmandad and Sterman, 2008). For the Bass model, efforts to explain changes in parameter estimates due to underlying heterogeneity of the population were also made (e.g. Bemmaor and Lee, 2002). Nevertheless, the fundamental issue that Bass-type models are not sufficient for hypothesis testing about the process that drives adoption behavior remains, since aggregate fit of models based on different theoretical assumptions (e.g., heterogeneity vs. information spreading mechanisms) are often indistinguishable (Emmanouilides and Davies, 2007).

Disregard of the structure of social interactions Due to the parsimonious structure of aggregate models, it is not possible to distinguish effects of different social processes on diffusion. In the Bass model, for example, the internal influence parameter p is often interpreted as word-of-mouth (hereafter WoM). However, it can also capture imitation effects such as social learning, social pressures, or network effects (Van den Bulte and Stremersch, 2004). Furthermore, Bass-type models make very specific assumptions about the structure of social interactions. The formulation implies a fully-connected social network in which everyone in the target population is directly connected to everyone else, and can potentially influence all others (Shaikh et al., 2006). It also presumes that the influence of adopters on non-adopters is a linear function of the number of adopters throughout the diffusion periods (ibid.). Because of these simplifying assumptions, the coefficient of imitation cannot be expected to directly reflect the underlying social mechanisms that shape diffusion processes.

Prescriptive guidance In their general typology of explicative models, Evered (1976) draw attention to *"the almost paradoxical contrast between the future-oriented nature of what practicing managers actually do, and the past-oriented nature of most of our scientific theories."* Traditional diffusion models illustrate this contrast. Managers planning the introduction of a new product are interested in predicting the effects of the decision variables at their disposal, most notably the marketing mix factors product, price, promotion, and distribution, none of which were initially considered explicitly in early diffusion models. This issue has been recognized and various authors have included marketing mix variables into aggregate diffusion models in order to better describe reality and potentially provide directions for how to alter the diffusion process by manipulating those variables (Ruiz-Conde et al., 2006).

In particular, marketing mix variables considered include price (Robinson and Lakhani, 1975; Bass, 1980; Feichtinger, 1982; Kalish, 1985; Jain and Rao, 1990; Bass et al., 1994, 2000), distribution and supply restrictions (Jones and Ritz, 1991; Jain et al., 1991; Jones and Ritz, 1991), and promotion and advertising (Dodson and Muller, 1978; Horsky and Simon, 1983; Kalish, 1985; Simon and Sebastian, 1987; Dockner and Jorgensen, 1988; Bass et al., 1994).

Two basic approaches for incorporating these variables are (i) via a separable, or (ii) via a non-separable function (Ruiz-Conde et al., 2006). The former specification assumes that marketing variables have a direct effect on sales, separate from the part that describes the diffusion process. The non-separable specification, by contrast, assumes that the marketing variables moderate the diffusion process, so that both parts cannot be separately included in the model.

In the Bass model, marketing mix is typically incorporated by means of a nonseparable function that makes p and/or q dependent on explanatory marketing variables, i.e., $p(t) = f(\text{marketing variables}(t))$ and/or $q(t) = f(\text{marketing variables}(t))$. In the former case, marketing variables affect the adoption decision via external influence, whereas in the latter case, they stimulate interpersonal communication. Some models also consider the effect of marketing on the size of the potential market (m). For a comprehensive review of marketing variables in macro-level diffusion models, we refer to Ruiz-Conde et al. (2006).

Although traditional aggregate models that include marketing mix variables have become highly sophisticated, there appears to be no consensus on what marketing variables to include and in which part of the models to include them (Ruiz-Conde et al., 2006). Furthermore, the incorporation of prices into models of innovation diffusion failed to significantly enhance the explanatory power of those models (Bottomley and Fildes, 1998).

Most of these extended traditional models can also be criticized for their structural meagerness, since there is usually no feedback between management decisions, which are defined as exogenous variables, and the diffusion of the product (Maier, 1998). To a large extent, the proposed extended models are monopolistic or branch models and exclude competition, repeat purchases, and substitution processes. As Meade and Islam (2006) note in their 25 year review, it is also fair to say that in most of these contributions, the emphasis has still been on the explanation of past behavior rather than on forecasting future behavior. The general approach has thus remained more descriptive than normative (Delre et al., 2007a) and extended aggregate models still provide limited potential policy (what-if) analyses and decision support.

2.1.2. System dynamics models

In order to overcome some of these limitations, innovation diffusion modeling has been approached from a system dynamics perspective. This perspective is characterized by a strong emphasis on feedback structures and non-intuitive secondary effects, as exemplified by Maier's (1998, p. 288-289) criticism that *"traditional models of innovation diffusion are sufficient for* *description and – under restrictive assumptions – for optimization, but they are insufficient for improving the understanding of complex and dynamic feedback structures in the field of innovation management"*. In the following, we outline characteristic features of the approach, present a system dynamics formulation of the Bass model, and briefly review diffusion models that appeared in the system dynamics literature.

2.1.2.1. Characteristics of System Dynamics

Like traditional parsimonious diffusion models, system dynamics models operate on the macro-level of analysis and hence do not allow for the explicit modeling of individuals' behavior. Unlike traditional models, however, they have the potential to consider a rich set of structural elements that influence the process of innovation diffusion and that could not be considered simultaneously in traditional models due to their methodological restrictions. In particular, Maier (1998, p. 289-290) lists four relevant elements that influence the process of innovation diffusion: (i) market structure (monopolistic, dynamic, oligopolistic), (ii) factors directly influenced by management decisions (pricing, advertising, quality of the product etc.), (iii) more general aspects that imply structural adjustments (substitution among successive product generations, potential repeat purchases, a time-varying market potential, negative word-of-mouth), and (iv) the process of innovation diffusion itself.

System dynamics is a methodology for complex systems analysis that is inherently oriented toward learning and problem-solving. Diffusion models based on this methodology emphasize decision-making and potentially allow decision-makers to assess new product introduction policies while taking the reaction of competitors into account (Milling, 1996). All elements, including managerial decisions, are typically conceived as endogenous variables of the market system rather than exogenous parameters of the model (cf. Milling, 1996). Figure 2.3 illustrates the elementary feedback structures of a typical system dynamics model of innovation diffusion proposed by Maier (1998). As can be seen from the figure, this model endogenizes a number of aspects that are either considered exogenous parameters or not considered at all in parsimonious analytical models. In particular, the firms' internal management decision variables, including R&D budgets, advertising, price, production, quality control etc. are typically not considered in most models of innovation diffusion.

This far-reaching definition of problem boundary illustrates that the system dynamics approach does not result in a single definitive model that provides clear-cut answers for a wide range of similar problems, but must be understood as a process that neither starts nor ends with the formulation and execution of a model. System dynamics is rather an *iterative* process that encompasses (i) the description of the system, (ii) conversion of the description to level and rate equations, (iii) design of alternative policies and structures (i.e., models), (iv) simulation of the model, (v) education and debate, and (vi) implementation of changes (cf. Forrester, 1994).

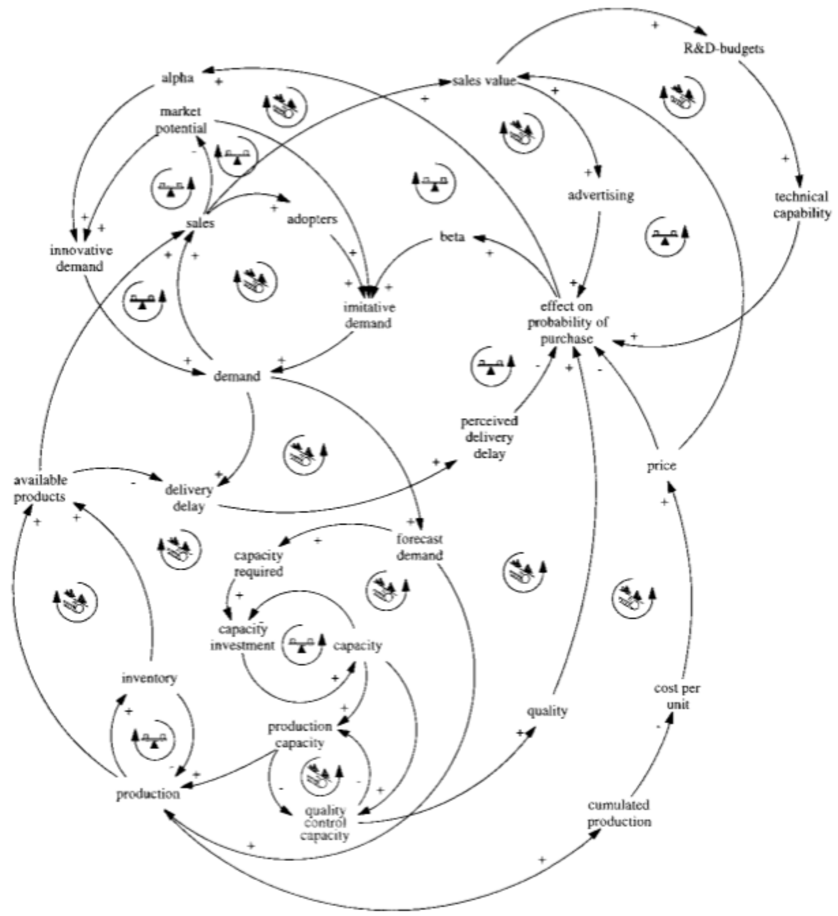


Figure 2.3.: Elementary feedback structures of a comprehensive system dynamics model of innovation diffusion (Source: Maier, 1998, p. 292)

2.1.2.2. The Bass model from a system dynamics perspective

To illustrate the modeling approach, we briefly review the Bass model from a system dynamics perspective by outlining a structurally identical model, following Maier (1998). A more thorough introduction to system dynamics modeling that also includes a system dynamics implementation of a Bass-type diffusion model can be found in Sterman (2001).

We start by specifying that the state of the market system is characterized by two variables: remaining market potential N_t and the number of adopters X_t. Sales in a period consists of innovative and imitative demand, which increase the number of adopters and simultaneously reduce the remaining market potential. This formulation of positive reinforcement and balancing negative feedback loops is characteristic for the system dynamics approach. The coarse structure of the model is illustrated by the stock and flow diagram in Figure 2.4. This type of diagram illustrates how stocks (i.e., entities that accumulate or deplete over time) are influenced and interconnected by flows (i.e., rates of change).

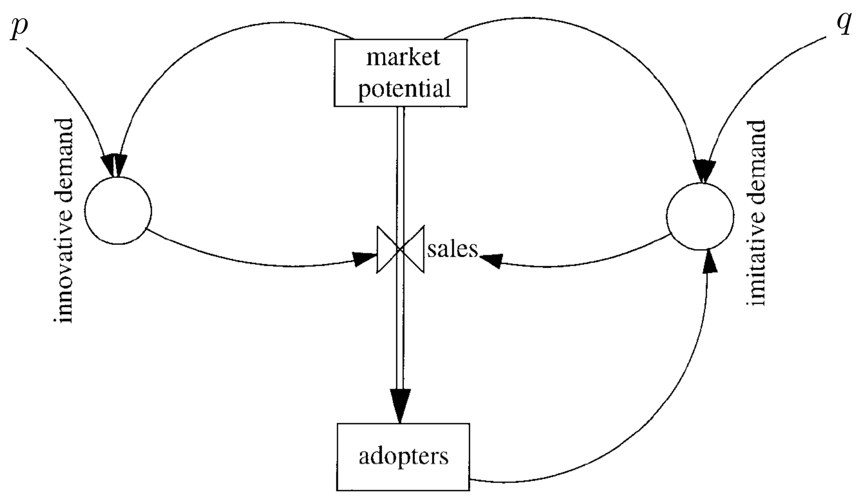


Figure 2.4.: Stock and flow diagram of a system dynamics formulation of the Bass model (Source: adapted from Maier, 1998, p. 291)

Formally, the influences illustrated in Figure 2.4 can be captured by a set of model equations. The two stocks in the model, which together determine the state of the system, are market potential (N_t) and adopters (X_t). The flow between the two stocks (i.e., sales) is determined by two loops: imitative and innovative demand. Innovative demand is given by

$$\text{innovative demand}_t = pN_t, \tag{2.3}$$

whereas imitative demand is defined as

$$\text{imitative demand}_t = \frac{X_t}{M} qN_t, \tag{2.4}$$

where M denotes the market potential.

To obtain results and gain an understanding of the dynamic behavior of the system, system dynamics models are typically implemented in software and executed on a computer. Simulation of the model outlined above yields the typical Bell-shaped adoption curve and sigmoid cumulative diffusion curve.

2.1.2.3. System dynamics diffusion models in the literature

The earliest application of the systems dynamics methodology in the context of innovation diffusion appears to be the model developed by Milling (1986). The author proposes a general and relatively simple model of monopolistic innovation diffusion and presents an application to pricing strategies in a dynamic environment. Milling (1996) builds upon this earlier work and investigates the timing of innovations. The author also proposes the use of the model developed in management gaming simulations.

Maier (1998) introduces a comprehensive model that considers competition as well as substitution among successive product generations. The elementary feedback structures of this model are illustrated in Figure 2.3. The model is intended to provide normative decision support by integrating feedback-dependent decision variables.

Mooy et al. (2004) propose a system dynamics diffusion model based on memetics theory with the aim of predicting the uptake of innovations within specific target consumer markets. They combine the Bass model with a classic epidemiologic SIR (Susceptible, Infectious, Recovered/Removed) model and highlight that their model can not only predict the shape of the diffusion curve, but also its height. A potential disadvantage of their approach is that estimation of the five main model parameters appears challenging.

More recently, various authors have developed system dynamics diffusion models for specific applications such as movie marketing (Lane and Husemann, 2004), hydrogen vehicle and refueling infrastructure diffusion (Meyer and Winebrake, 2009), and the diffusion of energy-efficient innovations in the residential building environment (Groesser et al., 2010).

2.2. Disaggregate models of innovation diffusion

Long before the adoption of agent-based modeling gained momentum in the social sciences, Eliashberg et al. (1986, p. 176) suggested that *"diffusion models that start at the microlevel have a rich potential in terms of a better understanding of the diffusion process and as a tool for managerial action."* Mahajan et al. also advocated an individual-level modeling approach to *"study the actual pattern of social communication, and its impact on product perceptions, preferences and ultimate adoption"* (Mahajan et al., 1990, p. 20).

Whereas aggregate diffusion models forecast the total market response, typically measured by the number of adopters who purchase the innovation by a certain time t, disaggregate models specify adoption decisions at the individual level. In these models, total market response is determined by aggregating demand from individual "smart" consumers that are not necessarily homogeneous and not just carriers of information (cf. Mahajan et al., 1979), but make deliberate decisions independently. Furthermore, individuals are not necessarily homogeneous. Disaggregate diffusion models are therefore more behaviorally based than aggregate models, which investigate relations between variables only on the macro level.

Three broad categories of disaggregate diffusion models can be distinguished: (i) microeconomic models, (ii) stochastic brand choice models, and (iii) agent-based simulation models, which have emerged more recently. In the remainder of this section, a brief overview of each category is provided. The following chapters will then focus exclusively on agent-based modeling.

2.2.1. Micro-economic models

Micro-economic models typically assume that individual consumers behave in a neoclassical microeconomic way (cf. Mahajan et al., 1979). Rather than postulating perfect information and homogeneity, however, these models allow for heterogeneity with respects to determinants of adoption, such as learning or varying preferences, across the population.

Most of these models were introduced before the easy access to computational power made numerical approaches viable on a large scale. For the sake of analytical tractability, they typically require specific assumptions about the distribution of attributes in the population. In many of these models, normal or beta-distributed values are assumed. The models proposed by Hiebert (1974), Feder and O'Mara (1982), Jensen (1982), and Oren and Schwartz (1988) are typical contributions in the micro-economic modeling tradition. Potential adopters are assumed to maximize an objective function (e.g., expected utility), taking into account the uncertainty associated with their understanding of the innovation's attributes, its price, pressure from other adopters to adopt it, and their own budget (Mahajan et al., 1990). In this line of research, Hiebert (1974) made early efforts to model uncertainty and learning in an innovation diffusion context. They characterize the effect of risk attitude and learning under uncertainty on the individual level of adoption without modeling interactions or aggregating to the macro-level. The model is formulated in an agricultural innovation context in which farmers are assumed to maximize expected utility and reduce uncertainty via learning.

Most other micro-economic models (Feder and O'Mara, 1982; Jensen, 1982; Oren and Schwartz, 1988) are based on Bayesian updating of uncertain perceptions. Feder and O'Mara (1982) introduce a model of agricultural technology adoption in which normally distributed initial perceptions are assumed. Furthermore, individuals are assumed to adopt if the expected profit exceeds the profit from current technology. Jensen (1982) considers diffusion in a heterogeneous population too, but assumes that perceptions are binary (i.e., an innovation is either profitable or unprofitable). In both models, potential adopters are assumed to be risk neutral. Oren and Schwartz (1988) assume a constant flow of risk averse consumers that adopt once the expected utility for a new product exceeds the expected utility of a current product. Perceptions about the performance of the product are initially assumed to be beta-distributed.

Micro-economic models offer valuable insights and inspiration but most of them cannot be applied directly to model or forecast diffusion processes, since they do not provide explicit functions for aggregate diffusion but focus exclusively on the micro-level. An exception is the model put forth by Chatterjee and Eliashberg (1990), who provide a closed formulation of the interface between individual and aggregate level to link individual decision-making and aggregate dynamics. Their model is based on specific heterogeneity assumptions and considers benefit perception of the innovation, personal preference, and the perceived reliability of information as individual-level determinants of adoption.

2.2.2. Stochastic brand choice models

A related stream of research can be found in the marketing literature, where dynamic extensions of stochastic brand choice models have a long research tradition. These models describe individual brand selection probabilities statistically in a discrete choice framework by means of multinomial logit models. For a general overview of stochastic models of consumer behavior in marketing, including brand choice and purchase incidence models, we refer to Wagner and Taudes (1987). For a review that specifically focuses on brand choice models, we refer to Manrai (1995).

Classic brand choice models offer a static portrait of how consumer choices are made and are hence limited to the study of markets in equilibrium (i.e., contexts in which consumers' preferences for alternatives can be reasonably assumed to be stationary, cf. Meyer and Sathi, 1985). Early efforts towards dynamic extensions for analyzing situations with "an unfamiliar array of products" were made by Meyer and Sathi (1985). In their model, consumers form expectations of product value given only limited information. They revise their evaluation of brands (i.e., expected utilities) in light of experiences gained through choice. This mechanism is incorporated by means of (non-Bayesian) updating functions.

Similarly, Roberts and Urban (1988) propose a dynamic brand choice model for consumer durables based on a Neumann-Morgenstern expected utility framework and Bayesian updating of beliefs about the value of brands. Again, a multinomial logit formulation links preferences to brand choice.

Dynamic brand choice models, such as the examples given above, can be applied usefully in situations where innovations fit into existing product categories and replacement largely determines the total market size. However, they provide limited potential for modeling the diffusion of innovations that consumers are not already familiar with because they lack elementary diffusion mechanisms such as communication.

2.2.3. Agent-based simulation models

The disaggregate frameworks developed in the micro-economic and discrete choice traditions hinge on specific assumptions about the distribution of individual-level consumer characteristics and/or limited analysis of aggregated variables. These models cannot capture nonlinear phenomena that typically emerge from the interaction of individual behaviors in diffusion processes. Micro-economic and discrete-choice models also cannot incorporate heterogeneity in terms of linkages in the social network and hence do not fully recognize the nature of innovation diffusion processes. Although they are relevant for diffusion modeling and describe the dynamics of individual behavior, neither of the approaches provides fully specified diffusion models. Microeconomic models are usually limited to the analysis of rational individuals' decisions on the micro-level, but do not incorporate diffusion processes on the macro-level. Stochastic brand choice models are also unsuitable for modeling the diffusion of major innovations (cf. Roberts and Urban, 1988), because they typically assume a constant market potential. Estimation of these models requires detailed micro-level data.

Agent based modeling and simulation (ABMS) is an approach that may potentially overcome these limitations, as well as the limitations of aggregate approaches outlined in Section 2.1. It is a bottom-up modeling approach that aims to capture emergent phenomena in complex systems on the macro-level by simulating the behavior and interactions of entities on the micro-level. Hence, a key distinguishing feature of this approach is that it does not examine relationships between macro-level variables directly, but rather aims to capture the behavior of individuals explicitly by modeling the rules they employ and the interactions they engage in, with the aim of obtaining a bottom-up causal model. In agent-based models, the elementary unit of modeling is therefore not the (complex) system as a whole, but rather the individual, or agent. This modeling paradigm has been applied to a broad range of problems in a various fields. Some illustrative examples are swarm insect behavior (Reynolds, 1987), ecosystems management (Bousquet and Page, 2004), land use change (Matthews et al., 2007), urban residential dynamics (Benenson, 2004), pedestrian movements (Turner and Penn, 2002), traffic management (France and Ghorbani, 2003), epidemiology (Auchincloss and Roux, 2008), and criminology (Malleson, 2010).

In the context of innovation diffusion, an important advantage of agent-based models lies in their ability to capture the complex structures and dynamics of diffusion processes without knowing the exact (and typically complex) global interdependencies (Borshchev and Fillipov, 2004). Moreover, an agent-based approach makes it possible to account for micro-level drivers of innovation adoption by modeling how consumers' attitudes and behaviors are affected by, for instance, the perception of product characteristics or information exchanged in a social network. Finally, the approach differs fundamentally from other aggregate and disaggregate diffusion modeling approaches in that it is not limited in its capacity to account for heterogeneity and social structure. Chatterjee and Eliashberg's model discussed in the previous section generated much interest on the impact of heterogeneity on innovation diffusion. This issue had been a matter of long-standing discussion in innovation diffusion research during the last decades (cf. Rogers, 1976), but due to methodological limitations, it remained largely untackled until the advent of ABMS.

In the following, we provide an agent-based formulation of the Bass model to illustrate differences in modelling and in how results are obtained. We thereby demonstrate that the Bass model is a special case that can also be captured by an analogous agent-based model. This model consists of M agents indexed by $i = 1, \ldots, M$, each of which is in either of two states: "potential adopter" or "adopter". We use a set of variables $x = (x_i, \ldots, x_M) \in \{0, 1\}$ to describe the agents' adoption state (i.e., $x_i = 1$ iff agent i has adopted).

In the Bass model, each actor's probability to adopt at time $t + \Delta t$, given that it has not adopted by time t, is described by the hazard model in Equation 2.1. In the analogous agent-based formulation in discrete time, we can use agents' explicit state variable x_i rather than the cumulative distribution function of adoptions $F(t)$. Agent i's probability to transition from non-adopter to adopter state is given as a function of the state of the system X as follows:

$$f(X) = \left(p + \frac{\sum_{i=1,\ldots,M} x_i}{M} q\right)(1 - x_i) \tag{2.5}$$

Analogously to the Bass model, the probability of agent i to adopt, given that it has not adopted so far, depends linearly on an independent external influence p and an internal influence q that depends of the fraction of prior adopters. The formulation implies homogeneity and global interconnectedness, i.e., each agent's individual probability of adoption is influenced uniformly by the adoption state of all other agents. Obviously, $f(x) = 0 \; \forall \; i$ for which $x_i = 1$ and $f(x) \in [0,1] \; \forall \; i$ for which $x_i = 0$, i.e., all agent that already have adopted remain in adopter state and all agents that have not adopted may switch their state with the same probability in the current period.

In Algorithm 1, we provide the agent-based formulation of the Bass model. Whereas the differential equation the Bass model is based on is defined in continuous time, most agent-based models are formulated in discrete time, i.e., time is divided into discrete simulation periods, and an algorithm is executed each period to determine changes in the state of the system. An important issue in such discrete time models is the choice of updating regime, i.e., how to determine the sequence of actions within each period. This issue is discussed in more detail in Subsection 4.2.1 in the context of the design of the model introduced in the present thesis. In our agent-based formulation of the Bass model, we use synchronized updating, which is the most commonly used approach. It avoids the issue by making agents' state changes a function of the state of the system in the previous period; if this mechanism is used, the sequence in which agents' states are updated does not matter. Algorithm 1 presents a discrete time/synchronous updating formulation of the Bass model. The latter is achieved by a temporary variable $\bar{x}$ which is used to store the new state of the system until the end of the period, when the actual updating occurs.

In each time period t until the simulation horizon T, the algorithm decides for each agent i whether or not it adopts based on the adoption probability according to Equation 2.5 and a random value *rand* drawn from $X(\omega) \sim U(0,1)$ (lines 7-8). If an agent adopts, the temporary variable $\bar{x}$ is updated accordingly (line 9). As soon as all agents have made their adoption decisions, the state of the system is updated (line 12). Then, the cumulative number of adopters by time t is determined by summing over x (line 13) and stored in a vector *adoptions*, which

Algorithm 1 Agent-based formulation of the Bass model

Require: number of agents M, external influence p, internal influence q, T

1: $x = (x_1, \ldots, x_M) \leftarrow (0, \ldots, 0)$
2: $\bar{x} = (\bar{x}_1, \ldots, \bar{x}_M) \leftarrow (0, \ldots, 0)$
3: //Iterate over time
4: **for** $t = 1 \rightarrow T$ **do**
5:     //Iterate over agents
6:     **for all** $i = 1 \rightarrow M$ **do**
7:         $p(adopt) \leftarrow \left(p + q\frac{\sum_{x_i=1,\ldots,M}}{M}\right)(1 - x_i)$
8:         **if** $rand = X(\omega) \sim U(0,1) \leq p(adopt)$ **then**
9:             $\bar{x}_i \leftarrow 1$
10:         **end if**
11:     **end for**
12:     $x \leftarrow \bar{x}$
13:     $adoptions_t \leftarrow \sum_{i=1,\ldots,M} x_i$
14: **end for**
15: **return** $adoptions$

the algorithm returns after iterating over all periods (line 15).

To derive findings, a stochastic ABM[1] is typically implemented as a simulation program and executed multiple times with varying random seeds to obtain a distribution of outcomes. Hence, a stochastic agent-based model does not provide a single analytical solution, but captures uncertainty and variability.

Figure 2.5 illustrates a Bass diffusion curve as well the diffusion curves of 25 replications of the analogous agent-based simulation with the same parameter setting. For this very special and simple stochastic model, the differential equation formulation of the Bass model provides an analytical solution. However, if the agent-based model becomes only slightly more complex (e.g., by introducing heterogeneity, social structure etc.), the equivalent system of differential equations can usually not be solved in closed form.

ABMs allow modelers to overcome these limits of mathematical tractability. The bottom-up modeling approach can easily incorporate arbitrary interaction mechanisms, micro-level drivers of adoption, bounded rationality, imperfect information, and individuals' heterogeneity in terms

[1] Most agent-based include stochastic elements. Hence the method is typically referred to as agent-based modeling and simulation.

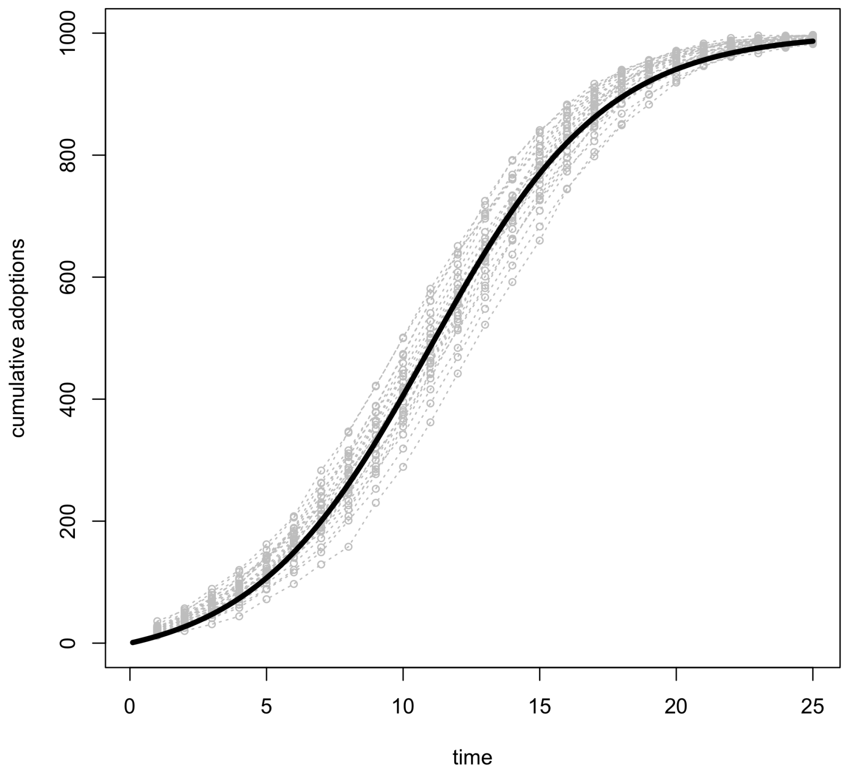


Figure 2.5.: Bass diffusion curve (solid) and 25 replications of the equivalent agent-based formulation (dotted) for $p = 0.01$, $q = 0.3$, $M = 1000$.

of attributes, behavior, and linkages in the social network. Hence, agent-based models have the potential to explain complex non-linear diffusion patterns observed in real world markets as the result of relatively simple local micro-level interactions. The following chapter first provides a general introduction to ABMS and then focuses specifically on agent-based models of innovation diffusion, providing a review of the relevant literature, identifying potential agent-based modeling approaches, and discussing findings that agent-based diffusion models have contributed so far.

3. Review of Agent-based Modeling in Diffusion Research*

Whereas innovation diffusion models and their applications have been reviewed extensively over the past 30 years (Mahajan and Muller, 1979; Mahajan et al., 1990; Sultan et al., 1990; Parker, 1994; Mahajan et al., 1995, 2000; Meade and Islam, 2006; Peres et al., 2010), these reviews have so far tended to focus exclusively on aggregate approaches and largely neglected agent-based diffusion models. Other related literature reviews have outlined (potential) uses of ABMs in innovation/new product development research (Garcia, 2005), and reviewed agent-based computational economics models of innovation and technological change (Dawid, 2006), but literature on agent-based modeling of innovation diffusion has not yet been the subject of a comprehensive review.

This chapter is structured as follows. Section 3.1 provides a general introduction to agent-based modeling and simulation and its role as a promising methodological innovation in the social sciences. Sections 3.2 and 3.3 systematically review available strategies for modeling two key elements in all agent-based diffusion models, i.e., consumer adoption behavior and social influence. Section 3.4 proceeds to review theoretical findings contributed through agent-based diffusion modeling, and Section 3.5 reviews applications and policy analyses.

Among the 47 research articles we could identify for our review in peer-reviewed journals, the majority of contributions (30) fall into the former category since they are mainly concerned with theoretical issues. However, the stream of applied literature has recently grown rapidly. To quantify this comment, we compared the average age of papers in both categories and found that as of 2011 it was 5.13 years for theoretical papers and 2.67 years for applied papers. These numbers highlight that the field as a whole is still in its infancy and that applied papers have on average appeared more recently.

Because of the highly interdisciplinary nature of agent-based diffusion research, we were also interested in the distribution of contributions among fields. To this end, we classified the papers

* Parts of this chapter will also appear in the following joint publication (the author of this thesis is also the lead author of that paper):

Kiesling E., Stummer C., Günther M., Wakolbinger L.M. (2011),
Agent-based simulation of innovation diffusion: A review,
Central European Journal of Operations Research, forthcoming.
DOI 10.1007/s10100-011-0210-y

reviewed by their journals category. The categories were defined as appeared most appropriate for the purpose of the review and neither represent a complete list of relevant fields, nor are they free of any overlaps. The rationale for the chosen categorization was to break down fields into subfields (e.g., innovation, marketing, forecasting) where possible and using broader categories (e.g., economics, business, operations research) where the number of contributions considered was more limited or for papers that could not be assigned to a more specific subfield. The result of this categorization is summarized in Table 3.1, which allows us to draw some interesting conclusions. We find that Marketing has been a particularly active field in that the majority of theoretical papers appeared in Marketing journals. However, to the best of this authors knowledge, no applied research papers appeared in Marketing journals so far. This might be interpreted as an indicator that the use of an agent-based methodology for practical purposes in that field would be an interesting new research approach. Applied research papers were mainly published in Innovation, Economics, or Energy and Environment journals. The broad spectrum of categories highlights the interdisciplinary nature of diffusion research.

	Theory		Application	
Innovation	3	(6.67%)	3	(6.67%)
Economics	3	(6.67%)	3	(6.67%)
Marketing	5	(11.11%)	0	
Business (misc.)	3	(6.67%)	2	(4.44%)
Operations Research	3	(6.67%)	1	(2.22%)
Forecasting	3	(6.67%)	1	(2.22%)
Sociology/Social Simulation	1	(2.22%)	1	(2.22%)
Energy/ Environment	0		3	(6.67%)
Physics	3	(6.67%)	0	
Other	6	(13.33%)	1	(2.22%)
Total	32	(68%)	15	(32%)

Table 3.1.: Papers reviewed by journal category

3.1. Agent-based modeling and simulation in the social sciences

In recent years, agent-based modeling and simulation has increasingly been applied in diffusion research to overcome limitations of aggregate models and open up new research opportunities. This trend is in line with a broader development in the social sciences, where the adoption of simulation methods in general, and agent-based simulation in particular, has gained momentum in recent years (cf., Chen and Yang, 2010; Squazzoni, 2010). Whereas numerical approaches have found widespread use in most scientific disciplines within the last 30 years, their acceptance in the social sciences has been limit until the mid-1990s, when seminal contributions by Gilbert and Doran (1994), Carley and Prietula (1994), Gilbert and Conte (1995), Casti (1996), Epstein and

Axelrod (1996), Hegselmann et al. (1996), Axelrod (1997), and Conte et al. (1997), among others, established "social simulation" as a multidisciplinary and fast-moving field at the intersection between social sciences and computer simulation (Davidsson, 2002; Squazzoni, 2010). For a general introduction to simulation in the social sciences, we refer to Axelrod (2007). A good overview of the intellectual structure of social simulation and its development is provided in Meyer et al. (2009).

Agent-based modeling and simulation, the pivotal methodological technique in social simulation, has been used as a tool to investigate a wide range of issues. Illustrative examples for widely studied topics are social dilemmas and sustainability (e.g., Jager et al., 2000; Koole et al., 2001; Jager et al., 2002; Gotts et al., 2003; Jager and Mosler, 2007; Janssen et al., 2009), segregation and residential dynamics (e.g., Schelling, 1969; Abdou and Gilbert, 2009), public opinion and attitude dynamics (e.g., Deffuant et al., 2002a; Hegselmann and Krause, 2002; Amblard and Deffuant, 2004; Jager and Amblard, 2005; Deffuant and Huet, 2007; Lopez-Pintado and Watts, 2008; Martins, 2008; Malarz et al., 2011), and demographic developments (e.g., Billari and Prskawetz, 2003; Billari et al., 2007), to name just a few. In economics and finance, agent-based methods (typically referred to as "agent-based computational economics" and "agent-based computational finance", respectively, in those fields) have also been developed very actively in recent years (for an introduction, cf., Tesfatsion, 2001, 2006; LeBaron, 2006, respectively). More unusual applications, as for example "binge" drinking as a social network phenomenon (Ormerod and Wiltshire, 2009), clustering and fighting in two-party crowds (Jager et al., 2001), or sociological implications of gift exchange (Alam et al., 2005), illustrate the wide range of social issues that may be tackled with agent-based methods. In the remainder of this section, we will introduce the agent-based methodology in a social sciences context by characterizing the term "agent", clarifying terminology, motivating the application of agent-based models for simulating social systems, discussing roots in cellular automata models of social systems, and explaining the typical solution approach.

What is an "agent"? Bonabeau (2002) argues that agent-based modeling is a mindset that consists of describing a system from the perspective of its constituent units rather than a technology. These micro-level constituent units of the system are called "agents" and may represent all kinds of actors such as, for example, insects in models of swarm behavior, vehicles in traffic simulations, individual members of an organization, firms in a simulated economy, or consumers in a simulated market. There is no universally accepted definition of what constitutes an "agent", and there are subtle differences in the definitions put forth in the wide range of different research schools that apply agent-based methods. However, several widely accepted key characteristics can be identified. Macy and Willer (2002) characterize agents as entities

- that exhibit autonomous behavior (i.e., not directed by any central authority),

- that are interdependent (i.e., they interact and exert behavioral influence upon each other),
- whose behavior is directed by simple rules on the micro-level, but produces complex behavior on the system level, and
- that exhibit adaptive and retrospective behavior based on learning from past experience.

A similar characterization in the artificial intelligence research tradition is provided by Weiss (1999, p. 1), who described an agent as *"... a computational entity such as a software program (...) that can be viewed as perceiving and acting upon its environment and that is autonomous in that its behavior at least partially depends on its own experience."* Windrum et al. (2007, 1.2) suggest that bounded rationality is also a key ingredient of social simulations.

A note on terminology As noted above, agent-based modeling approaches have been developed (partly independently) and adopted in several disciplines. As a consequence, there is no clear-cut definition of what an "agent" is, but there is also no consistent term for the approach itself. Agent-based methods are referred to by various names including "agent-based modeling", "agent-based simulation", agent-based modeling and simulation", "multi-agent (based) simulation", "individual-based modeling", "agent-based systems", and "multi-agent systems", among others (cf. Hare and Deadman, 2004, who make an attempt to disentangle terminology). Various disciplines have also established their own specific terms such as "agent-based social simulation", "agent-based computational economics", "agent-based computational finance", "artificial life", or "artificial markets". In this thesis, we will consistently use the term "agent-based modeling and simulation".

Motivation An essential characteristic of social simulation and the main reason why ABMS is useful in the social sciences is its ability to contribute to our understanding of emergent phenomena (Gilbert, 1995; Bonabeau, 2002; Gilbert, 2002b). In a social context, the philosophical notion of *emergence* describes the effect that *"collective phenomena are collaboratively created by individuals yet are not reducible to explanation in terms of individuals"* (Sawyer, 2001, p. 551). This important recognition is closely related to the idea that social systems are in fact *c*omplex systems whose macroscopic regularities are the dynamically emerging outcome of (relatively simple) micro-level interactions (cf. Sawyer, 2005). This interpretation of social dynamics as a type of computation (Epstein, 1999) provides a new conceptualization of the micro-macro link in sociology, which has been a matter of considerable debate for a long time (cf. Alexander et al., 1987). In particular, modeling social systems from the bottom up makes it possible to capture phenomena in which macrobehavior emerges from micromotives, as Schelling (1978) put it in his renowned book.

If social systems are in fact complex systems, a paradigm that is increasingly accepted among social scientists, then traditional reductionist research approaches may not be the most appropriate tools for studying them. Reductionist approaches are based on the idea of deconstructing the system under study into its constituent components in order to gain an understanding of the system-level behavior by analyzing the components individually. This approach is clearly doomed to fail when applied to systems characterized by aggregate complexity, i.e., systems defined more by the interactions between components than by the constituent parts themselves (cf. Manson, 2001). To illustrate the concept, swarming behavior (i.e., flocking, herding, shoaling) is frequently quoted as an example for an emergent phenomenon. The motion of a flock of birds, which may appear erratic and hard to describe at the system (i.e., flock) level, can be reproduced easily and convincingly by imposing a set of simple rules on each agent (i.e., individual bird) at the micro-level, as early computer graphics experiments by Reynolds demonstrated in 1987. The same holds true for many phenomena in the social sciences, the diffusion of innovations being a particularly prominent example.

Another important motivation for employing ABMS is that it allows researchers to study social phenomena through experimentation, which is typically not possible in real-world social systems (Axtell, 1999). "Growing" a computer representation of the social system by modeling it from bottom up provides a natural environment to study it (Bonabeau, 2002) by conducting what-if experiments and test the influence of various parameters and mechanisms on the process under study.

Furthermore, as opposed to many other methods, ABMS is not restricted to study only the equilibrium state of social systems (if such a state should exist), but by their very nature provide excellent opportunities to study the dynamics of these systems. This aspect is closely related to the idea of "generative social science", which follows the motto *"if you didn't grow it, you didn't explain its emergence."* (Epstein, 1999). Also, because ABMs are "solved" by executing them, an entire dynamical history of the process under study is obtained as a part of the solution process (Axtell, 1999).

The flexibility provided by agent-based models is another important benefit since it allows researchers to explicitly incorporate important aspects that could only be accounted for in highly stylized ways using other approaches. Examples for such important aspects include physical space and social networks, which matter in most social processes (Epstein, 1999; Axtell, 1999), as well as individuals' heterogeneity and bounded rationality.

To sum up, ABMS is particularly useful when (Bonabeau, 2002, p. 7,287)

- the interaction between individuals are complex, nonlinear, discontinuous, or discrete,
- space is crucial and agent's positions are not fixed,
- the population is heterogeneous,
- the topology of interactions is heterogeneous and complex, and/or
- individuals exhibit complex behavior, including learning and adaptation.

The diffusion of an innovation throughout a society is a phenomenon for which essentially all of these conditions apply.

Roots in cellular automata Agent-based modeling has its roots in the cellular automaton formalism (cf. Wolfram, 1986) which has a long tradition in the social sciences that can be traced at least back to Schelling's 1971 famous model of segregation dynamics. This model represents the diffusion of disadoption of a neighborhood ("white flight") based on heterogeneous tolerance thresholds of cells. Extending a prior, one-dimensional model (Schelling, 1969), Schelling used coins on a graph paper to model cells in a regular grid, each representing a resident that belongs to a distinct (e.g., ethnic) group. Residents have a heterogeneous tolerance level regarding the share of neighbors that belong to a different group. Once a neighborhood starts to become integrated, residents with a low threshold start to leave, thereby slightly decreasing the fraction of their own group in the neighborhood and inclining a few more residents to leave. Because this positive feedback cycle of segregation has a self-sustaining momentum, it is difficult to stop it once a critical threshold is reached. Thus, even if residents are relatively tolerant and have only a small preference for their neighbors to belong to the same group, segregation dynamics can lead to total segregation.

However, ABMs also differ from cellular automata in important respects. First, cells in a cellular automaton are typically characterized by a single finite state variable; agents' state, interaction, internal processing, and behavior, by contrast, tends to be more complex. Second, the structure of local interactions in a cellular automaton model is typically based on a regular lattice (e.g., von Neumann or Moore neighborhoods) whereas ABMs can be based on arbitrary local interaction structures. These and other differences notwithstanding, terminology in the literature is inconsistent and cellular models are frequently referred to as "agent-based". Since cellular automata also follow an individual-based approach, papers based on it were included in the review of the theoretical literature in Section 3.4.

"Solving" agent-based models A final point that should be made is that ABMS differ fundamentally from other modeling approaches not only in terms of modeling granularity, but also fundamentally in how the results are obtained. Rather than describing the whole system directly and "phenomenologically", macro-scale dynamics emerge when the model is executed. Rather than explicitly solving equations (analytically or numerically), agent-based models are therefore typically implemented in software. Agents are commonly implemented as objects that have states and rules of behavior. Results are obtained by means of simulation experiments, i.e., executing the implementation on a computer and analyzing the generated data, or as Axtell (1999) puts it, *"instantiating an agent population, letting agents interact, and monitoring what happens"*.

3.2. Modeling consumer adoption behavior

A pivotal element of agent-based diffusion models is the explicit representation of consumers' decision making processes, most importantly those related to the decision to adopt an innovation (or to reject it, which, however, is not considered explicitly in most models). A number of approaches have been developed to model these decisions, ranging from simple decision rules to sophisticated psychological models. In the following, we discuss the most common approaches.

3.2.1. Simple decision rules

Perhaps the simplest conceivable decision rule is to adopt as soon as the first of an agent's acquaintances has adopted. This rule can be interpreted as a contagious spread of information about the innovation. Threshold models use similar mechanisms, but typically stipulate that a consumer adopts only once a certain proportion of its acquaintances has adopted. The threshold is typically varied across the population and either deterministic, i.e., agents decide deterministically once the threshold is reached (e.g., Valente and Davis, 1999; Goldenberg et al., 2000; DeCanio et al., 2000; Alkemade and Castaldi, 2005), or probabilistic, i.e., agents adopt with a certain probability once the threshold is reached (e.g., Bohlmann et al., 2010).

Diffusion models in the economics literature (e.g., Kocsis and Kun, 2008; Hohnisch et al., 2008; Cantono and Silverberg, 2009; Faber et al., 2010) typically use simple decision rules based on cost minimization or heterogeneous reservation prices. These models frequently assume falling prices due to learning effects and tend to interpret social influence as benefits due to network externalities. These network externalities occur when the utility of a network good increases with the number of peers or the share of the market that has adopted (cf. David, 1985; Katz and Shapiro, 1986, 1992).

3.2.2. Utilitarian approaches

From a classical rational choice perspective, innovation diffusion phenomena pose an explanatory challenge. They do not fit directly into classical economic thinking because homogeneous, perfectly rational individuals acting in a perfect market with complete information would always adopt at the same time. If we acknowledge that individuals are neither homogeneous, nor perfectly informed, (expected) utility is an obvious candidate concept for modeling adoption decisions, given that it constitutes a key building block of standard microeconomic theory of individual choice behavior. One could therefore expect utility theoretic approaches to feature prevalently in the literature. Surprisingly, however, the number of contributions that analyze innovation diffusion in a utilitarian framework is limited. Many of them use "utility" as an interpretive tag rather than explicitly modeling the choice between a single or multiple innovations and non-adoption (i.e., utility of highest alternative opportunity) by means of utility functions that represent individual preferences. Delre et al. (2007a,b, 2010), for example, formulate threshold functions for individual utility based on heterogeneous "quality expectations" and social utility components to obtain a utility aspiration level for each consumer agent. Conceptually, their approach does not differ fundamentally from other threshold models, apart from the interpretation of thresholds as "utility aspiration levels". In a similar vein, Choi et al. (2010) introduce a fixed individual utility component which is interpreted as a "quality perception" and formulate social utility, which they interpret as benefits due to network externalities, as a linear function of the proportion of adopters in the neighborhood.

Few attempts have been made to integrate multi-attribute preference modeling approaches (for an introduction to multi-criteria decision making, cf. Keeney and Raiffa, 1993) into ABMs of innovation diffusion so far.

3.2.3. State transition approaches

A number of models represent adoption behavior by means of a single dichotomous variable that represents agents' external state, i.e., agents are either in a "potential adopter" or an "adopter" state. In this respect, state-transition-based innovation diffusion models differ from many infectious disease models, which are frequently referred to as an inspiration and analogy for innovation diffusion models, since these models typically use more than two states (e.g., SEIR - susceptible, exposed, infected, removed/recovered). Goldenberg and Efroni (2001), for example, model adoption as a probabilistic transition between two states that results either from spontaneous transformation or from WoM induced awareness.

Other models, by contrast, represent the decision making process as a sequence of transitions between more than two states. Goldenberg et al. (2007), for example, consider rejection explicitly and specify separate transition probabilities for adoption/rejection based on positive WoM, advertising, and negative WoM. Deffuant et al. (2005), use a fixed state transition scheme based on interest (no, maybe, yes) and information states (not-concerned, information request, no adoption, pre-adoption, adoption). Thiriot and Kant (2008) also model adoption decisions as a sequence of transitions between multiple states, viz. awareness, information seeking, adopter, WoM spreading.

3.2.4. Opinion dynamics approaches

Opinion dynamics in social systems have been studied intensively in recent years (Kocsis and Kun, 2008). For an introductory article, we refer to Hegselmann and Krause (2002). A number of innovation diffusion models have adopted ideas from the rich stream of opinion dynamics literature, stipulating that consumers develop preferences in a collective process of opinion formation. In a so-called CODA (continuous opinions, discrete actions) model put forward by Martins et al.

(2009), for example, each agent has a probabilistic opinion assigned to the proposition "A is the best choice that can be made". This opinion is updated by means of Bayesian interference based on observed adoption behavior of neighboring agents. Refusal in adopting is increasingly weighted by neighbor agents as evidence against the innovation. Deroïan (2002) simulates the emergence of a collective evaluation of an innovation based on individual propensities to adopt that are interpreted as opinions. The author incorporates the idea of "bounded confidence" (cf. Hegselmann and Krause, 2002) by assuming that consumers with similar opinions tend to form stronger bonds while those with very different opinions tend to diminish the level of received influence.

3.2.5. Social psychology approaches

Social psychology approaches, arguably the most sophisticated and least parsimonious, are based on psychological theories of behavior. Rather than representing consumers as instances of *homo economicus*, these models incorporate the behavioral richness exhibited by "homo psychologicus" in real life (Jager et al., 2000). Adoption decisions are therefore based on psychological rules rather than perfect rationality. For a comparison of the suitability of various social psychological theories for consumer agent design, we refer to Zhang and Nuttall (2011).

Ajzen's theory of planned behavior (TPB) is a commonly used theoretical foundation for modeling consumer agents' behavior in application- and policy-oriented diffusion models (cf. Ajzen, 1991). It postulates that attitude, perceived behavioral control, and intention are predictors of behavior. Kaufmann et al. (2009) use TPB to model the diffusion of organic farming practices. Agents (i.e., farmers) adopt if their intention exceeds an empirically derived threshold. Schwarz and Ernst (2009) use TPB as a framework to model consumers' decisions to adopt or reject water-saving innovations using two different kinds of decision rules: a cognitively demanding deliberate decision rule and a very simple decision heuristic. Zhang and Nuttall (2011) model smart metering adoption behavior based on TPB.

Another commonly used social psychological framework is the "consumat" approach developed by Jager et al. (2000). In this framework, consumer agents (so-called "consumats") switch between various cognitive strategies (viz. comparison, repetition, imitation, and deliberation) depending on their level of need satisfaction and their experienced degree of uncertainty. This approach has been used in various theory-oriented and applied models (Jager et al., 2000; Janssen and Jager, 2001; Schwoon, 2006).

3.2.6. Econometric estimation of choice probabilities

While theoretical models need to be less concerned with methods for initializing the simulation with empirical data, practical applications and policy analyses do require such methods.

Statistical methods can be used to model adoption behavior and facilitate parameterization. Dugundji and Gulyás (2008), for example, make use of pseudo-panel microdata to estimate individual adoption probabilities based on demographic characteristics, availability of alternatives, and percentage of agents' neighbors and socioeconomic peers that make each choice. Although correlational rather than theory-driven and behavioral, such econometric estimation approaches can be useful for applied models, although they do not offer deeper insights into causal mechanisms.

3.3. Modeling social influence

The critical relevance of social influence in the diffusion of innovations has been recognized for a long time and was considered early on in traditional differential equation models of innovation diffusion (e.g., through the internal influence parameter in the Bass model). ABMs offer researchers the opportunity to explicitly model the interactions that exert social influence, and thereby allow them to take the structure of social interactions into account. This is important, because, as remarked by Katz (1961), *"it is as unthinkable to study diffusion without some knowledge of the social structures in which potential adopters are located as it is to study blood circulation without adequate knowledge of the veins and arteries."* In this section, we systematically review approaches for modeling social influence by distinguishing three levels of influence and briefly reviewing the social network models typically used to structure interactions in agent-based diffusion models. Finally, we also cover qualitative approaches to model social influence.

3.3.1. Levels of social influence

Social influence is a generic concept that can operate on multiple levels. For the purpose of this review, we differentiate between micro-, meso-, and macro-level social influence.

3.3.1.1. Micro-level

Micro-level social influence is transmitted locally through pairwise communication links. word of mouth (WoM) is arguably the most relevant form of micro-level social influence. Evidence of its powerful role in the diffusion of innovations is well documented in both industry market research and scholarly research (e.g., Arndt, 1967; Reingen and Kernan, 1986; Brown and Reingen, 1987; Mahajan et al., 1990; Herr et al., 1991; Buttle, 1998). Many of the reviewed models incorporate positive WoM mechanisms, and a few of them (Moldovan and Goldenberg, 2004; Goldenberg et al., 2001; Deffuant et al., 2005) also consider negative WoM, which evidence suggests has a much stronger effect than positive WoM (Richins, 1983).

3.3.1.2. Meso-level

We define meso-level social influence as any influence that stems collectively from an agent's immediate social environment (i.e., neighborhood in the social network). Concepts associated with meso-level social influence include group conformism, social comparison, herding behavior, local network externalities, and conspicuous consumption, which holds that the intrinsic value of a products may be less important than the social meaning (Veblen, 1899). In many of the reviewed papers, the term "social influence" is used in the sense of meso-level social influence.

3.3.1.3. Macro-level

We define macro-level social influence as global interactions at the level of society as a whole. Examples for this type of influence include influence of the aggregate network-level opinion (e.g., Deroïan, 2002) or macroeconomic feedbacks (externalities) such as learning effects, which are based on cumulative sales (e.g., Hohnisch et al., 2008).

Figure 3.1 illustrates the levels of social influence modeled in each of the papers reviewed. The codes in the Venn diagram correspond to the codes listed in Table 3.3 (theoretical papers, listed as T1 – T30 and covered in **??**) and Table 3.4 (applied papers, listed as A1 – A15 and covered in Section 3.5), respectively. Most, but not all of the reviewed models incorporate social influence, and the levels of modeling vary widely among them. The majority of papers considers a single level, most commonly either the micro-level or the meso-level. Eight theoretical papers model social influence on two levels. Applied models, with the exception of Schwoon (2006) (A11) which considers meso- and macro-level influence, and Vag (2007) (A12) which considers all three levels, model only a single level of social influence.

3.3.2. Structural characteristics of social networks

Results of agent-based models typically depend critically on (i) which interactions occur between (ii) which agents in (iii) what sequence. In order to simulate micro- and meso-level social influence, modelers therefore need to carefully specify the topology of consumers' interactions by establishing links between them. The aggregation of these links forms a graph $G = (V, E)$ consisting of a set of vertices V that represent individuals, and a set of edges E that represents the relationships between them. This graph represents the social network in which interactions take place. Although the structure of social interactions in a society appears highly complex and variable, most, if not all, social networks share distinct features which recent work on social networks within mathematics and physics has identified (Newman, 2000, cf.). In this section, we briefly discuss these features before before outlining graph models that can be used for social network generation in simulation experiments.

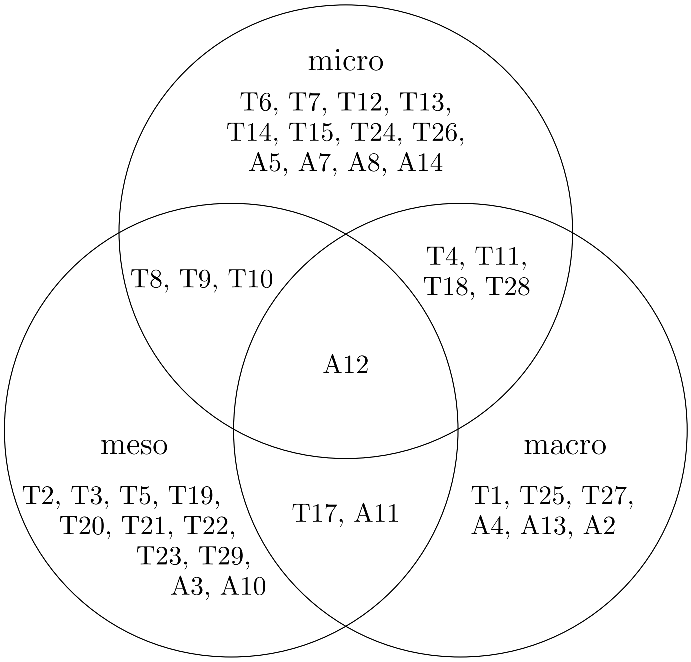


Figure 3.1.: Levels of social influence modeled in the papers reviewed

3.3.2.1. Small diameter and small characteristic path length

The *diameter* of a graph is defined as the largest number of links on the shortest path between any two nodes, where a "path" is defined as a sequence of distinct, connected nodes and the length of a path is measured by the number of nodes traversed. Formally, let $d(i, j)$ be the length of the shortest path between nodes i and j. The diameter of the network, frequently denoted $D(G)$, is then given by $\max_{i,j} d(i, j)$.

In small diameter networks, this length is constant or scales at most logarithmically with the number of nodes (Newman, 2000). In a social network context, the small diameter characteristic corresponds to the notion that any two individuals can be connected through a surprisingly small number of links. This characteristic feature has been confirmed in many sociometric studies, starting with Travers and Milgram's famous experiment (Travers and Milgram, 1969). In this experiment, US-participants in Omaha (Nebraska) and Wichita (Kansas) were asked to forward a letter to a recipient in Boston (Massachusetts). Individuals were instructed to forward the letter directly only if they knew the target and otherwise to forward it to friends or relatives that they knew personally and that were more likely to know the target. While most letters did not reach their destination (thus introducing non-response bias), the average path length of those that did arrive was approximately 5.5. Travers and Milgram did not speculate on global interconnectedness and did not use the term "six degrees of separation", which later became associated with the phenomenon, popularized by a play with the same title (Guare, 1990). Although Travers and Milgram's experiment and subsequent small world studies have been criticized on methodologic grounds (for an overview, cf. Schnettler, 2009a), the hypothesis that the diameter of social networks tends to be small remains widely accepted today (cf. Newman, 2000).

A closely related measure is the *characteristic path length* of a network. It is commonly denoted $L(G)$ and defined as follows (cf. Lovejoy and Loch, 2003): The average distance from a specific node i to all other nodes in the network is defined as $\overline{d} = \frac{1}{(n-1)} \sum_{j=1}^{n} d(i, j)$. The characteristic path length of the network is then defined as the average of these over all nodes in the network, i.e., $L(G) = \frac{1}{n} \sum_{i=1}^{n} \overline{d}(i)$.

3.3.2.2. High clustering

In highly clustered networks, the probability of a tie between two actors is much greater if the two entities in question have another mutual acquaintance, or several (Watts and Strogatz, 1998). Hence, high clustering implies that triadic closures are likely and that there is strong local correlation among links. In a social context, this means that networks tend to be "cliquish", i.e. i being linked to j as well as to k implies a strong likelihood that j is also linked to k. This corresponds to the notion that we are much more likely to be acquainted with a friend's friend than with any arbitrary person.

To measure the amount of clustering in a network, Watts and Strogatz (1998) define a *clustering coefficient*, frequently denoted $C(G)$, as the probability that two acquaintances of a randomly chosen person are themselves acquainted (Newman et al., 2002).[1] In a social context, clustering coefficients have intuitive meanings: a node's clustering coefficient reflects the extent to which its friends are also friends of each other whereas the average clustering coefficient of the network measures the cliquishness of a typical friendship circle (Watts and Strogatz, 1998). In a fully connected network, in which everyone knows everyone else, $C = 1$; in a random graph $C = z/N$ (where N denotes the number of nodes), which is very small for a large network Newman (2000).

Using this measure, Watts and Strogatz (1998) show that the collaboration graph of film actors exhibits very high clustering ($C = 0.79$). Other studies have since obtained similar results for other social networks such as scientific collaboration networks (typically $C = 0.3$ or greater, cf. Newman, 2001),

3.3.2.3. Small-world property

The term "small-world" is used in various ways that need to be carefully distinguished (Newman et al., 2002). First, the phrase "small-world (effect)" has been in colloquial use for a long time,

[1] More formally, the clustering coefficient is defined as follows (Watts and Strogatz, 1998): suppose that a node i has k_i neighbors; then at most $k_i(k_i - 1)/2$ edges can exist between them. The clustering coefficient C_i of a node i denotes the fraction of these allowable edges that actually exist. The clustering coefficient C is defined as the average of C_i over all i.

typically to comment on situations where two strangers discover that they have a mutual acquaintance. Second, Milgram (1967), based on an unpublished manuscript by Ithiel de Sola Pool and Manfred Kochen, defined the "small-world problem" more generally as the question of how many links there are on the connecting path of acquaintances between two people (Schnettler, 2009b, for a history of "small-world" research, cf.). Finally, Watts and Strogatz (1998) coined the related, but nevertheless distinct term "small-world networks" to refer to a class of networks that exhibit a combination of both high clustering *and* a small characteristic path length. Their contribution drew many physicists to the problem and triggered a new wave of network research (for reviews of recent work, cf. Barabási, 2002; Newman, 2003; Albert and Barabási, 2002). The latter definition is the most relevant in the context of this work to which we will refer in the context of network models below.

3.3.2.4. Scale-freeness property

A notable characteristic of many (but not all) social networks is that their degree distribution (where "degree" refers to a node's number of links) has a highly skewed form. In particular, the probability $P(k)$ that a node in the network is connected to k other nodes frequently decays as a power law, following $P(k) \sim k^{-\lambda}$ (Barabási et al., 1999). In a social context, this corresponds to the notion that some people have a much larger number of acquaintances than others. The collaboration graph of movie actors, for example, follows a power law with exponent $\lambda_{actor} = 2.3 \pm 0.1$ (Barabási et al., 1999). The probability that a scientific publication is cited k times (representing the connectivity of a paper within the network) follows a power law with exponent $\lambda_{cite} = 3$ (Redner, 1998). Networks of phone calls made during one day (i.e., telephone numbers which are connected by a link if a call has been made during a day) also show scale-free behavior; Aiello et al. (2000) find that their degree distribution follows a power law with an exponent of $\lambda_{phone} = 2.1$. The nodes of an e-mail network (i.e., e-mail addresses which are connected by a link if an e-mail has been exchanged between them) has been found to obey a power law with exponent $\lambda_{email} = 1.81$ (Ebel et al., 2002).

3.3.2.5. Strength of weak ties

Granovetter's highly influential "strength of weak ties" theory (Granovetter, 1973) distinguishes between two types of social bonds – weak and strong ties – based on their structural characteristics. The theory asserts that our acquaintances ("weak ties") are less likely to be socially involved with one another than are our close friends ("strong ties"). As a consequence, weak ties are not merely trivial acquaintance ties, but rather serve as a *"crucial bridge between densely knit clumps of close friends"* (p. 202 Granovetter, 1983).

Granovetter originally introduced the theory by showing that when searching for a job, strong ties are much more helpful than weak ties because the information close friends receive overlaps considerably with what we already know. Acquaintances, by contrast, know people that we do not, and thus receive more novel information (Granovetter, 2005). The concept may be particularly relevant in the diffusion of innovations because weak ties pave the path for the spread of information throughout society by unlocking and exposing interpersonal networks to external influences (Goldenberg et al., 2001).

3.3.3. Network models

One possible approach to create a simulated social environment is to construct it directly by mapping a real social network. To this end, necessary data can be obtained, for example, through interviews, surveys, or observation. This sociometric approach has a long tradition in empirical diffusion research starting with Coleman et al.'s seminal study on the diffusion of an new drug among physicians (Coleman et al., 1957). Their research design was aimed at tracing out the links by which each doctor was connected with the rest of the medical community and included all the local doctors in whose specialities the new drug was of major potential significance. The authors thereby obtained an almost complete sample of the social network relevant for the spread of the innovation. However, since real-world networks are often quite large, an empirical mapping of a social network is usually infeasible (Bohlmann et al., 2010), which presumably is the reason why the approach has, to the best of our knowledge, not been used for social network parameterization in agent-based diffusion modeling so far.

Mapping-based approaches may become more viable in the future as individuals increasingly communicate as well as explicitly declare their social relationships in large-scale online social websites, and as new methods that facilitate large-scale sampling of the generated data are developed. However, detailed data on individuals' interactions usually still is, and probably will remain, publicly unavailable. Furthermore, this data is also not necessarily appropriate and sufficient for use in diffusion models, since it only covers a fraction of individuals' relevant social interactions (i.e., only certain kinds of online interactions). Finally, for large populations, it may remain impractical to sample the whole network and represent each individual as an agent.

An interesting alternative methodology to construct simulated networks on the basis of survey data is proposed by van Eck and Jager (2010). Their algorithm creates a corresponding agent for every respondent and uses survey data to construct appropriate links. In particular, the approach requires that information on the number and kinds of relations (e.g., normative vs. informational, similar vs. dissimilar for each relation) of each respondent is available. Using error indicators that measure the deviation from agents' current relations to the relations specified in the survey data, the algorithm optimizes the network to approximate the structure of links on the individual level as closely as possible.

The most common alternative approach is to approximate social networks with artificial, stylized graph models that exhibit the same essential structural characteristics. Due to the practical challenges involved in directly representing real-world social networks, this approach has become common practice in agent-based social simulation. Some models use complete graphs or lattice-based topologies to structure interactions. Others rely on a number of generative algorithms developed in physics and mathematics to systematically create graphs that reproduce characteristic features of social networks such as those outlined in the previous section. In the following, we discuss network models that are most commonly used in agent-based social simulations in general, and agent-based diffusion models in particular.

3.3.3.1. Complete graphs

Whereas aggregate model formulations such as the Bass model typically imply a fully-connected social network, ABMs can use arbitrary interaction topologies that capture characteristics of real world social networks. While most agent-based models proposed in the literature take advantage of this methodological strength, some of them do not and limit their analysis to complete graphs or include them for comparison. Including complete graphs could be particularly helpful for "docking" agent-based models with the Bass model. Model "docking" is the process of "aligning" two models and determining whether they can produce the same results and, in turn, whether one model can subsume another (Axtell et al., 1995). So far, hardly any attempts have been made to dock agent-based diffusion models with aggregate diffusion models. An exception is Rahmandad and Sterman (2008), which compares agent-based and differential equation models. However, the authors model the spread of a contagious disease and therefore do not incorporate deliberate adoption decisions.

3.3.3.2. Lattice-based topologies

Square lattice topologies are used prevalently to structure the interaction of cells in cellular automata models. The discrete two-dimensional space from which the topology is derived may represent a real geographic or an abstract space. In the absence of any natural boundaries, periodic boundary conditions are frequently used to simulate an infinite lattice. In a two-dimensional lattice, this is achieved by connecting top and bottom cells as well as the left and right edges. The space can then be thought of as being mapped onto a three-dimensional torus. Most commonly, cells are either connected to the four cells in the von Neumann neighborhood, i.e., those cells orthogonally surrounding them (North, East, South, West), or to the eight cells in the Moore neighborhood, i.e., all cells surrounding them (i.e., N, E, S, W, NE, SE, SW, NW). The fixed number of neighbors per cell (four or eight) and the completely regular structure of these topologies, both of which are not typically found in real-world social networks, limits their potential for social network modeling.

Some cellular automata models proposed in the diffusion modeling literature have introduced alternative approaches to incorporate characteristics of real-world social networks into lattice-based networks. Goldenberg et al. (2001, 2007), for example, incorporate ideas from Granovetter's "strength of weak ties" theory (Granovetter, 1973). In their models, each individual belongs to a single personal network connected by strong ties, but also performs a number of random weak tie interactions with individuals outside their personal network each period. Generalizations and extensions to higher dimensions are also possible, but they have not been used in a diffusion modeling context so far.

While there are a number of models that are based on a complete graph or a lattice structure, the majority of ABMs proposed in the literature relies on generative algorithms to systematically create graphs that reproduce characteristic features of real-world social networks. The remainder of this section describes the most commonly used algorithms.

3.3.3.3. Random graphs

One of the first and most general generative graph algorithms is the random graph model introduced by Gilbert (1959) and, more commonly acknowledged, by Erdős and Rényi (1960). This graph model is used prevalently in diffusion models and often serves as a baseline for comparisons with other network structures. It is perhaps the simplest possible model that describes a wide range of networks from unconnected to fully connected and can generate all possible networks for a given number of vertices and edges. The diameter of the resulting random graphs tends to be small, i.e., the largest number of links on the shortest path between any two nodes is small, which is a characteristic the generated graphs share with most real-world social networks (Travers and Milgram, 1969). Unlike social networks in reality, however, random graphs are typically not highly clustered, although highly clustered graph instances can occur with very small probability since the algorithm can generate all possible graphs. Random networks are also typically not scale-free, but their degree rather converges to a Poisson distribution.

3.3.3.4. Small-world networks

As has been noted above, networks that are both highly clustered and have a small characteristic path length, are called *small-world networks*. Instances of this network class can be generated by means of an algorithm introduced in Watts and Strogatz (1998), which interpolates between random graphs and completely ordered lattices.

Because of the generated graphs' topological similarities with real-world social networks, they are frequently used in ABMs of innovation diffusion (cf. Table 3.3). It has to be noted, however, that these graphs do not reproduce the scale-freeness property described in Subsection 3.3.2, which social networks also exhibit in many cases.

Network model	small diameter	high clustering	scale-free
Complete graphs	yes	no	no
Low-dimensional regular lattices	no	yes	no
Random (Erdős and Rényi, 1960)	yes	no	no
Small-world (Watts and Strogatz, 1998)	yes	yes	no
Scale-free (Barabási et al., 1999)	yes	no	yes

Table 3.2.: Network models and typical social network characteristics reproduced

3.3.3.5. Scale-free networks

A network model that captures the scale-freeness characteristic was proposed by Barabási and Albert (1999). It starts with a few connected nodes; nodes are added one by one and attached to existing nodes with probabilities according to the degree of the target node. Therefore, the more connected a node is, the more likely it is to receive new links, which is called a "preferential attachment" rule. The resulting networks are scale-free, but typically not highly clustered. This algorithm is also used in several agent-based diffusion models (cf. Table 3.3).

Table 3.2 summarizes the network models introduced above by indicating which of the common social network characteristics the generated graphs typically reproduce. Approaches to capture all three main desirable features (small diameter, high clustering, scale-freeness) in a single model have also been proposed (e.g., Dorogovtsev et al., 2002), but they have not been introduced in the agent-based diffusion modeling literature so far. For a broader survey of general social network modeling approaches, which also covers sociological approaches based on statistical models and dynamic approaches where the relationships are generated by the agents themselves, we refer to Amblard (2002). Algorithms that have been incorporated in the simulation model described in this thesis are specified in Subsection 4.3.5.

3.3.4. Qualitative modeling of social influence

Most agent-based diffusion models incorporate social influence either as the spread of awareness of an innovation, positive or negative WoM, or by considering the share of adopters in the agent's network neighborhood when making adoption decisions. Thiriot and Kant (2008) propose an entirely different approach which allows them to study social representations of innovations. They formalize beliefs and messages as associative networks that consist of directed associations between concepts. Consumer agents embody a belief base, a list of currently salient social objects, and are linked to an agent profile which contains the default exposure to mass channels, background knowledge, and subjective production of knowledge. Agents communicate and exchange messages, which contain transmissible associative networks that may cause them to revise their beliefs.

Kim et al. (2011) also suggest a different approach to qualitatively model characteristics of an innovation and their communication. They argue that available product information is frequently subjective and imprecise and apply fuzzy set theory to transform linguistic product evaluations on multiple cost and benefit attributes into crisp numbers. When evaluating the overall performance of each available product, agents incorporate information obtained from neighbors that have adopted a product into their evaluation through graded mean integration.

3.4. Review of theoretical findings

We identified four major areas of research which form the structure for our review of theoretical findings: (i) impact of consumer heterogeneity on innovation diffusion, (ii) role of social influence in diffusion processes, (iii) effectiveness of promotional strategies, and (iv) endogenous innovation and competitive diffusion. Each of these four areas leverages a specific methodological strength of agent-based modeling, viz. (i) the ability to explicitly model decision making entities individually, (ii) the ability to account for the interactions between them, (iii) the ability to address what-if-type questions, and (iv) the ability to capture emergent market dynamics.

In cases where a paper's contributions fall into more than one of these four subject areas, findings are discussed separately in the respective subsections. Table 3.3 provides an overview of the theoretical papers reviewed and specifies for each paper the modeling of agents' adoption decision making and the interaction topologies used.

Code	Reference	Agent decision-making	Interaction topology
T1	Abrahamson and Rosenkopf (1997)	threshold based on individual assessment and "bandwagon pressure"	densely-linked "core stratum" + weakly-linked "peripheral stratum"
T2	Alkemade and Castaldi (2005)	exposure and over-exposure threshold (neighborhood)	k-regular; random; small-world
T3	Bohlmann et al. (2010)	probabilistic threshold (neighborhood)	lattice; random; small-world; scale-free
T4	Cantono and Silverberg (2009)	price below individual reservation price	lattice with periodic boundary conditions
T5	Choi et al. (2010)	utility (individual + network effects)	small-world
T7	Deffuant et al. (2005)	fixed state transition scheme based on interest and information states	small-world
T8	Delre et al. (2007a)	threshold function (individual preference and social influence part)	small-world
T9	Delre et al. (2007b)	threshold function (individual preference and social influence part)	small-world
T10	Delre et al. (2010)	individual and social utility thresholds; total utility adoption threshold	regular lattice; scale-free with a faster decay of the number of links; undirected/directed and unweighted/weighted;
T11	Deroïan (2002)	evolving (based on homophily) directed graph (influence links, also negative influence - inhibitive)	propensity to adopt based on expected utility (interpreted as an individual opinion)

Code	Reference	Agent decision-making	Interaction topology
T12	Goldenberg and Efroni (2001)	random spontaneous; word-of-mouth induced based on the number of neighboring adopters	lattice
T13	Goldenberg et al. (2001)	probabilities for becoming informed through weak-tie w-o-m, strong-tie w-o-m and exposure to marketing efforts	lattice
T14	Goldenberg et al. (2000)	heterogeneous individual utility threshold	multidimensional (2-5) lattice
T15	Goldenberg et al. (2007)	probabilities of being influenced by positive word-of-mouth, advertising, and/or negative word-of-mouth	"dynamic small-world" with changing weak ties
T16	Goldenberg et al. (2009)	probabilistic adoption (either because of wom or advertising)	none, no explicit social network, but probabilities for adoption as a consequence of w-o-m
T17	Goldenberg et al. (2010a)	adopt if the global network externality threshold level is exceeded and w-o-m is received	square lattice (Moore neighborhood)
T18	Hohnisch et al. (2008)	price below heterogeneous reservation price (time-dependent in the extended model)	lattice
T19	Janssen and Jager (2001)	"consumat" approach (cf. Jager et al., 2000)	small-world
T20	Janssen and Jager (2002)	"consumat" approach (cf. Jager et al., 2000), social and personal needs	small-world
T21	Janssen and Jager (2003)	"consumat" approach (cf. Jager et al., 2000)	small-world; scale-free
T22	Kocsis and Kun (2008)	local cost minimization in the presence of network effects	square lattice with random rewiring (small-world)
T23	Kuandykov and Sokolov (2010)	fraction of adopters in the neighborhood; 2 fitting parameters	random; 3 clusters with random internal and external links; scale free
T24	Martins et al. (2009)	continuous opinions, discrete actions (CODA); Bayesian interference	square lattice with random rewiring (small-world);
T25	Moldovan and Goldenberg (2004)	adoption and rejection are result of positive w-o-m/advertising or negative w-o-m (with a specified probability)	none
T26	Rahmandad and Sterman (2008)	passive agents; state changes at stochastic rates	fully connected; random; small-world; scale-free; lattice
T27	Schramm et al. (2010)	individual adoption threshold as a function of feature, price, promotion and social influence	none
T28	Thiriot and Kant (2008)	awareness - information search - adoption (not formally specified)	small-world
T29	Valente and Davis (1999)	threshold of neighbors	random allocation of ties
T30	van Eck et al. (2011)	threshold function (individual preference and social influence part)	scale-free

Table 3.3.: Modeling of agent-decision making and interaction topologies

3.4.1. Consumer heterogeneity

A key strength of ABMs is that they overcome the homogeneity assumption of traditional aggregate diffusion models. This section reviews the progress in understanding the impact of consumers' heterogeneity made possible through ABMs.

3.4.1.1. Heterogeneity in propensity to adopt

The most common approach to incorporate consumers' heterogeneity is to specify it in terms of an intrinsic "propensity to adopt", typically through heterogeneous adoption thresholds drawn from a distribution. One of the first micro-simulation studies to investigate heterogeneity in this manner was conducted by Goldenberg et al. (2000). They propose a cellular automaton model in which cells are characterized by an adoption threshold that is randomly drawn between zero and one and interpreted as a "quality expectation". The spread of an innovation with a certain fixed "product quality" is modeled spatially on a lattice in which cells decide whether or not to adopt once a sufficient number of neighboring cells have adopted. Simulation results exhibit strong fluctuations in sales and suggest that heterogeneity may have a strong influence on innovation diffusion.

Delre et al. (2007a,b, 2010) also use heterogeneous adoption thresholds in their models. They interpret these thresholds as "utility aspiration levels" and specify them as weighted sums (with heterogeneous weighting factors) of two separate threshold functions: (1) a social utility threshold, i.e., a minimum fraction of adopters in the social neighborhood, and (2) a utility threshold function based on agents' heterogeneous "quality expectation". They find that increasing heterogeneity accelerates diffusion because the critical mass is reached sooner than in homogeneous populations (Delre et al., 2007b).

In addition to an adoption ("exposure") threshold, Alkemade and Castaldi (2005) introduce an "over-exposure" threshold to incorporate the idea that innovations tend to be considered no longer "fashionable" once their user base becomes too large. Each agent adopts when the proportion of adopters in their neighborhood exceeds its exposure threshold, but remains below its over-exposure threshold. Heterogeneity in both thresholds is introduced by drawing the exposure threshold from a uniform distribution and adding a fixed value to obtain the over-exposure threshold. While heterogeneity is incorporated in the model, the effect of varying degrees of heterogeneity are not analyzed in the paper.

3.4.1.2. Heterogeneity in reservation prices

A conceptually different, but structurally very similar approach is to model heterogeneity in terms of varying individual reservation prices. Cantono and Silverberg (2009) follow this approach and investigate the path of diffusion of a new energy technology when some consumers are willing to pay more for goods that are perceived as "green". Agents adopt once any of their neighbors has adopted *and* the price falls below their individual reservation price drawn from a lognormal distribution. Learning economies reduce the price as a function of the extent of previous adoption, which may lead to delayed adoption for a certain range of initial conditions. Results indicate that a limited subsidy policy may trigger diffusion that would otherwise not happen when reservation prices are heterogeneous, learning economies are in a certain range, and initial price levels are high.

Hohnisch et al. (2008) model heterogeneous reservation prices too, but draw them uniformly and independently. Agents adopt once the price falls below their reservation price, which is interpreted as a subjective "individual valuation". The authors also formulate an extended model in which these "individual valuations" are time-dependent. They explain the empirical finding of a delayed "take-off" of a new product by a drift of the percolation dynamics from a non-percolating regime to a percolating regime which occurs because the probability of buying increases over time with the cumulative number of buyers. Heterogeneity in reservation prices plays a critical role in this process and determines whether diffusion takes place or fails.

3.4.1.3. Heterogeneity in communication behavior

In a comparison of agent-based and differential equation-based diffusion models, Rahmandad and Sterman (2008) investigate the impact of heterogeneity in terms of contact frequency. They model the spread of a contagious disease and therefore do not incorporate deliberate adoption decisions, but rather model adoption as state changes triggered by a stochastic processes. Nevertheless, they stress that results extend beyond epidemiology to innovation adoption. With respect to heterogeneity in individual contact rates, they find that it causes slightly earlier mean peak times as high-contact individuals rapidly seed the epidemic, followed by lower diffusion levels as the high-contact individuals are removed, leaving those with lower average transmission probability and a smaller reproduction rate. Note, however, that although the authors emphasize the transferability of results, caution is required when translating these findings to an innovation diffusion context.

3.4.1.4. Socio-demographic heterogeneity

A more empirically-oriented approach to represent heterogeneity in propensity to adopt is to link it directly to individuals' socio-demographic characteristics. While such an approach compromises explanatory power, it has the advantage that empirical data (if available) can be used more easily. Dugundji and Gulyás (2008) follow this approach in investigating the impact of heterogeneity on the adoption of transportation mode alternatives and use empirical pseudo-panel micro data to parameterize their model. They consider both observed heterogeneity (in terms of sociodemographic characteristics, individual-specific attributes of the choice alternatives, and the availability of alternatives) and unobserved heterogeneity (in terms of common unobserved attributes of the choice alternatives in the error structure of their econometric estimation model). They find that heterogeneity has a dramatic impact on the magnitude of the transportation mode shares, on the speed of the transition to a steady state, and very fundamentally on the number of possible observable steady-state solutions and conclude that *"heterogeneity cannot be ignored in any true empirical application"* (Dugundji and Gulyás, 2008, p. 1051). Policy implications of the study are examined in Subsection 3.5.2.

In all of the papers referred to above, heterogeneity is found to affect the diffusion of innovations considerably. It may cause fluctuations in sales, delay take-off, result in irregular diffusion patterns that deviate significantly from the typical s-shaped curve, and explain diffusion failure, all of which are phenomena that are frequently observed in the diffusion of real products.

3.4.2. Structural effect of social network topology

Innovation diffusion cannot be explained as a result of individual heterogeneity alone, but it is also fundamentally a social process (Rogers, 2003). The effect of the structure of links in consumers' social network, through which awareness, information, and opinions about an innovation are spread, is one of the most intensively researched topics in the agent-based innovation diffusion literature. Advances in network modeling and the development of generative algorithms for small-world (Watts and Strogatz, 1998) and scale-free (Barabási and Albert, 1999) networks have strongly stimulated research in this area. In the following, we group papers by the topologies being compared.

3.4.2.1. Small-world vs. regular vs. random networks

A number of authors (Alkemade and Castaldi, 2005; Delre et al., 2007b; Kocsis and Kun, 2008; Martins et al., 2009; Choi et al., 2010) have analyzed diffusion in small-world networks with varying degrees of randomness (i.e., interpolations between regular and random networks, cf. Watts and Strogatz, 1998). Alkemade and Castaldi (2005) compare diffusion in regular, random, and small-world networks and vary network density as well as "exposure" thresholds (i.e., minimum proportion of adopters in the neighborhood) and "over-exposure" thresholds (i.e., maximum proportion of adopters in the neighborhood). The latter thresholds inhibit adoption if the proportion of adopters in the social neighborhood is already too large for it to still be "fashionable". Results indicate that in a sparse network cascades occur even when consumers' exposure threshold is high. As the network density increases, cascades become more unlikely and the critical exposure threshold becomes smaller. The authors find that the critical exposure thresholds are similar for small-world and regular networks. On the random network, no cascades occur if the density is sufficiently low, because the network becomes disconnected.

Delre et al. (2007b) also compare various interpolations between regular and random networks, but base their model on different assumptions. They do not consider "overexposure" and model agents' decision making by means of a threshold function that consists of an individual utility part (obtained if the quality of the innovation exceeds a threshold) and a social utility part (obtained if the fraction of adopters in the agent's social neighborhood exceeds a threshold). Results indicate that innovations diffuse faster in more regular (i.e., clustered) networks than in random networks because individuals are exposed to more social influence and may therefore decide to adopt sooner. As a unique contribution among all reviewed papers, the authors also investigate how the dimension of personal networks (i.e., 1 = only direct first acquaintances, 2 = direct first acquaintances and their acquaintances etc.) affects the diffusion and conclude that bigger personal networks are associated with slower diffusion, particularly in random networks.

A different modeling approach is taken by Kocsis and Kun (2008), who focus on the diffusion of telecommunications technology, an industry characterized by strong positive network externalities. They develop an opinion dynamics model in which adoption decisions depend on a cost minimization procedure that is based on the number of agents in the personal network that decide to adopt or reject a technology. The proposed model constructs a small-world type network starting from a square lattice topology with periodic boundary conditions and randomly rewiring edges. The authors vary the share of rewired edges and find that in the presence of network externalities, rewired edges (i.e., increasing randomness) can facilitate but can also hinder diffusion, depending on how advantageous the advanced technologies are in comparison with the lower level ones.

In many of the reviewed models, agents' decision to adopt is considered a signal in favor of an innovation by neighboring agents. An interesting approach is to also interpret neighbors' refusal to adopt as evidence against the product. Martins et al. (2009) formulate a model that incorporates this idea by means of a Bayesian system. To examine the impact of small-world effects, they conduct experiments with a regular square lattice topology and varying degrees of random rewiring. Results show that more rewiring (i.e., a higher degree of randomness) is associated with faster diffusion and an increased final proportion of adopters, which contradicts results by Kocsis and Kun (2008). This can be explained by the differing modeling assumptions. Whereas Kocsis and Kun (2008) model only positive feedback effects due to externalities, Martins et al. (2009) also implicitly model a "diffusion of rejection", which may spread faster in more clustered networks. The authors also study the influence of the location of early adopters, comparing instances of clustered vs. randomly scattered "seed" adopters (1% of the population) and find that the process of innovation diffusion from an initial cluster is much slower than in the case of randomly spread adopters.

Motivated by the question why diffusion sometimes propagates throughout the whole population and why at other times it halts in its interim process, Choi et al. (2010) study the diffusion of network products in random and small-world networks. They specify the consumers' willingness to adopt as a function of the product's intrinsic value perceived by each consumer (normally distributed constant) and the benefit due to local network effects based on the proportion of adopters in the agent's neighborhood. In line with results of Kocsis and Kun (2008), they find that network structure plays a moderator role for the link between network effects (i.e., positive externalities of adoption) and innovation diffusion. Results also suggest that a new product is less likely to reach full diffusion in random networks than in cliquish networks because randomness in the topology makes it harder for an innovation to build up network benefits at the initial stage. However, once the diffusion process reaches a critical mass, diffusion grows faster in a random network.

3.4.2.2. Scale-free vs. random

Scale-free network topologies (Barabási and Albert, 1999) attracted considerable interest, although somewhat less than small-world networks, which appear to be more appropriate interaction models for many (but not all) markets. Kuandykov and Sokolov (2010) focus exclusively on comparing the diffusion in scale-free and random networks. In their model, consumers adopt with a probability that is determined by the fraction of adopters in the neighborhood and two fitting parameters that control time to adoption start and S-curve steepness, respectively. System behavior and the resulting shape of the diffusion curve are a direct consequence of the choice of these two aggregate-level parameters. Based on (only) one single replication per condition analyzed in the paper, the authors observe faster adoption for a random network compared to a scale-free network with the same number of nodes. However, time to full adoption in the random network tends to grow with the number of links. Results also indicate that innovation spreads remarkably faster through what the authors refer to as a "clustered random network" (a network in which agents are distributed among three clusters that are then connected sequentially) than through one uniform cluster with the same total population and the same number of initial adopters.

3.4.2.3. Small-world vs. scale-free vs. random

Few authors have compared all three of the most common network topologies so far. Pioneering research that compared the effect of small-world and scale-free networks on market dynamics was conducted by Janssen and Jager (2003). They model agents' behavior from a social psychology perspective and adopt the "consumat" approach (Jager et al., 2000), which incorporates alternative assumptions on behavioral rules. The proposed model simulates market dynamics that emerge from agents' choice between multiple products which are replaced as soon as they become unprofitable. It is not a dedicated diffusion model, but results relate to innovation diffusion nonetheless. Findings indicate that a scale-free network leads to a market dominated by far fewer products as opposed to a small-world network. Results also show that in scale-free networks, a small proportion of consumers (hubs, or early adopters) may have an exceptional influence on the consumptive behavior of others.

Rahmandad and Sterman (2008), while primarily concerned with comparing stochastic agent-based and deterministic differential equation models, also study the impact of different network structures. In particular, they compare fully connected, random, small-world, scale-free and lattice networks. In line with previous research, they find that higher clustering slows diffusion to other regions, because it increases the overlap in contacts among neighbors. In the small-world and regular lattice networks, this leads, on average, to lower peak prevalence and higher peak times. Because the model is concerned with the spread of contagious diseases, one should be cautious when interpreting results from an innovation diffusion perspective.

One of the most comprehensive studies on the impact of social network topology to date was conducted by Bohlmann et al. (2010), who compare diffusion in cellular (Moore neighborhood), random, small-world, and scale-free networks. Furthermore, they also study how the strength of communication links between two market segments – an innovator segment and a follower segment – affects diffusion. They formulate a model with probabilistic adoption ($p = 0.5$) when a threshold (proportion of adopting neighbors) is reached. By varying this adoption threshold, the authors find that it affects the likelihood of diffusion cascades differently among the various network structures: diffusion appears more likely in clustered networks under high adoption thresholds. The random network exhibits more consistent peak adoption across threshold levels. Moreover, the effect of network structure becomes more significant when agents' adoption threshold increases. For the two-segment model with varying link strength between innovator and follower market segments, results unsurprisingly indicate that an early emphasis on innovator adoptions rather than innovator-to-follower communications can speed market adoption when follower communications are weak. The authors conclude that network topologies are a key factor in determining an innovation diffusion process and its pattern and that in particular highly clustered networks can have substantially different diffusion patterns than more randomly connected networks.

3.4.2.4. Other network topologies

In an early contribution, Abrahamson and Rosenkopf (1997) first suggest that a focus on social networks could enrich theories that explain the timing and extent of innovations' diffusions. Their social network model is based on a densely-linked core stratum and a weakly-linked peripheral stratum. Depending on initial adopters' location, they distinguish between "trickle-down" diffusion processes, which emanate from core strata, and "trickle-up" processes that originate from the peripheral strata. The former tend to diffuse innovations congruent with network norms while the latter tend to diffuse contra-normative or competence-destroying innovations. Agents adopt if their individual assessment and a “bandwagon pressure” exceeds an agent-specific threshold. The authors use small-sized networks with only 21 nodes and vary density and structure of links in and between core and peripheral strata. Simulating both trickle-down and trickle-up diffusion processes, they find that small, seemingly insignificant idiosyncrasies of network structures can have large effects on the extent of an innovation’s diffusion. These results have important implications that are not fully elaborated upon in the paper. In particular, the findings suggest that it may be more appropriate to tackle questions in diffusion research with modern complexity theory rather than with deterministic differential equations.

In order to model the effect of social hubs in the diffusion process, Delre et al. (2010) test the impact of the number of contacts as well as degree and direction to which social influences determine individual’s choice to adopt. Like in previous work (Delre et al., 2007a,b), agents’ decision making is based on heterogeneous utility thresholds defined as the sum of social and individual utility parts. However, unlike in prior contributions, the authors use “broad-scale” networks (Amaral et al., 2000), i.e., scale-free networks with a cut-off parameter (faster decay of the number of links) to structure interactions and motivate this with constraints people often have in building links with other people. Furthermore, their approach differs from prior work in that connections can be directed and weighted. In particular, they assume that the influence of a neighbor is proportional to the number of links it has and that the probability of directing the link from i to j depends on the number of links that i and j have. Results demonstrate that social influences can have a positive effect on the diffusion of the innovation if a given critical mass is reached, but also can have a negative effect otherwise. Social influence may decrease the chances for the diffusion to spread significantly if the innovation is of lower quality (i.e., induces less individual utility) and thus hardly reaches the critical mass. Uncertainty about the innovation success therefore increases in more socially susceptible markets. These results dissent with the common intuition that fashionable markets are easy to penetrate because consumers tend to copy each other. When the weights are stronger for those neighbors that have more relationships, the innovation reaches higher degrees of penetration. However, this effect is relatively small compared to other network factors. The direction of the relationships among consumers does not substantially affect the final market penetration. Finally, results indicate that innovations have, on average, fewer chances to spread in markets with high social influence.

3.4.2.5. Strong vs. weak ties

Adopting Granovetter’s “strength of weak ties” theory (Granovetter, 1973, , cf. Subsection 3.3.2), Goldenberg et al. (2001) break down the personal communication between closer and stronger communications that are within an individual’s own personal group (strong ties) and weaker and less personal communications that an individual has with a wide set of other acquaintances and colleagues (weak ties). They formulate a cellular automata model that does not explicitly represent agents' adoption decision processes, but rather models the spread of information about an innovation by means of probabilistic state changes of passive cells. The probability of an individual cell becoming informed is based on probabilities of becoming informed via weak-tie WoM, strong-tie WoM and exposure to marketing efforts. In their full factorial experimental design the authors systematically vary these three probabilities as well as the size of each individual's personal network and the number of weak tie contacts. Results indicate that the influence of weak ties on information dissemination is at least as strong as the influence of strong ties and that the process is dominated by WoM rather than by advertising.

Summarizing results of the reviewed studies, it can be concluded that the topology of the social network involved in consumers' decision making is consistently found to have a large impact on innovation diffusion. Random networks, as opposed to more regular or more clustered ones, tend to favor the spread of information and they are therefore frequently associated with faster diffusion and an increased share of adopters at the end of the diffusion process. However, in markets in which positive externalities of adoption or strong meso-level social influence (e.g., group conformism, herding behavior etc.) exist, diffusion appears to be both more likely and faster in more clustered networks. Social influences may have a positive or negative effect in these markets, depending on whether a given critical mass is reached. These markets are therefore more uncertain concerning the final success of the innovation.

In a nutshell, managers planning the introduction of an innovation should take into account that people participate in different networks for different markets and consider the characteristics of particular networks relevant for the product, since this may be a critical factor at the early market stage and determine whether a new product diffuses or fails. From a theory-building standpoint, the strong impact of network topologies implies that the careful selection of a network structure is crucial.

3.4.3. Network externalities

Network externalities (cf. Katz and Shapiro, 1986, 1992) have garned attention in the marketing literature (for an overview, cf. Stremersch et al., 2007) because they affect the diffusion of innovations in numerous industries including information technology, entertainment, and communications. The source of these externalities may be global or local, i.e., the utility of the innovation may depend on the proportion of adopters in the entire social system or in the local social neighborhood (Goldenberg et al., 2010a).

As noted in Subsection 3.4.2, Kocsis and Kun (2008) model local network effects in their opinion dynamics model of telecommunications technology. However, they do not use network externalities as an explanatory variable. Choi et al. (2010) also model the diffusion of network products, but they focus on the role of network structure and do not study the impact of network externalities in detail.

Goldenberg et al. (2010a), by contrast, focus specifically on the effect of network externalities and seek to analyze their absolute impact. To this end, they formulate both an agent-based and an aggregate model. In the ABM, consumers consider adoption only if the proportion of adopters in the population exceeds an agent-specific threshold drawn from a truncated normal distribution (this part of the formulation incorporates global network externalities). Once this threshold is exceeded, an agent adopts with a probability determined by two parameters. The first parameter controls the influence of the fraction of adopters in the agent's (Moore) neighborhood on a two-dimensional lattice (incorporates local network externalities), the other controls the influence of "external factors" such as advertising. The authors perform simulations with varying adoption threshold distributions and influence parameters, and demonstrate that network externalities consistently have a "chilling" effect on the profitability of new products. They substantiate this claim by formulating an aggregate model to which they fit empirical diffusion data on six network products and, thus, are able to confirm the "chilling" effect of externalities.

The paper by Goldenberg et al. sparked a vivid debate on agent-based approaches in marketing and on the substance and theoretical foundations of the contribution (Stremersch et al., 2010; Gatignon, 2010; Rust, 2010). On a substantive level, Stremersch et al. (2010) and Gatignon (2010) criticize that imposing the existence of a threshold on the network externalities process – which the authors aim to validate through theoretical reasoning – "loads the dice" in favor of finding chilling effects. They also question more generally whether the chosen individual level process is reasonable. Furthermore, they argue that the simplifications made to model it may lead to erroneous outcomes. Rust (2010) further questions the conclusions and argues that the construction of the model makes the substantive implications a foregone conclusion. In a rejoinder, Goldenberg et al. (2010b) respond to the criticism by defending the global threshold assumption. While no final conclusions can be drawn, it appears that a consensus has emerged from the discussion that future research on network externalities can benefit significantly from the flexibility provided by ABMs.

3.4.4. Negative word-of-mouth

The destructive potential of negative WoM has long been acknowledged (Richins, 1983), but its important role in innovation diffusion processes has been neglected in traditional models. To investigate the interplay between positive and negative WoM induced by opinion and resistance leaders, respectively, Moldovan and Goldenberg (2004) extend a previous model (Goldenberg et al., 2001) that focused exclusively on the role of strong and weak ties. In the extended model, consumers are in one of three states: uninformed (not spreading WoM), adopter (spreading positive WoM), or resistor (spreading negative WoM). The population is exogenously divided into three groups: (i) opinion leaders, who may only adopt the innovation, (ii) resistance leaders, who may only reject the innovation, and (iii) regular consumers subject to both positive and negative WoM. Adoption occurs, at a certain probability, as a result of positive WoM or advertising, while rejection occurs as a result of negative WoM. The social network is not modeled explicitly. Instead, global interconnectedness is assumed. The authors vary the proportion of opinion and resistance leaders in the market as well as the probabilities of being influenced by advertising and positive/negative WoM imparted by ordinary consumers, opinion leaders, and resistance leaders, respectively. As can be expected, results indicate that resistance leaders will reduce sales significantly, as a function of both their relative number and the strength of their social influence.

In a related contribution that also extends the model introduced in Goldenberg et al. (2001), Goldenberg et al. (2007) investigate the interplay of weak and strong ties with positive and negative WoM. Moreover, they link diffusion directly to the net present value of the firm. Again, adoption is not modeled as a deliberate decision process, but rather as a probabilistic transition between three states (adopt/reject/none), based on probabilities of being influenced by positive WoM, advertising, and/or negative WoM. The network used in the simulations is a dynamic small-world-type network that consists of both permanent strong ties and randomly changing weak ties. To create the experimental conditions, the authors vary size of strong ties and weak ties, percentage of disappointed consumers, and probability of being influenced by advertising and positive/negative WoM via strong/weak ties, respectively. Results indicate that the presence of weak ties, which is beneficial to the firm under normal circumstances, might adversely affect it in the presence of dissatisfied consumers. Even a small percentage of dissatisfied consumers can cause considerable damage to long-term profits, since they create an invisible diffusion of product rejection which may not be noticed immediately.

Deffuant et al. (2005) develop a model that simulates the formation of positive and negative opinions about an innovation and their spread via positive and negative WoM. In particular, they investigate the role of a minority of "extremists" with very definite opinions. The proposed model evolved from previous work in an agricultural context (Deffuant et al., 2002b); it differs significantly from the cellular automata based threshold-models outlined above. Rather than modeling passive automatons with a binary adoption state and stochastic state transitions, Deffuant et al. model agents' adoption behavior with a state transition scheme based on interest (no, maybe, yes) and information states (not-concerned, information request, no adoption, pre-adoption, adoption). Interest is based on social opinion, individual benefit and uncertainty intervals around these continuous values. Individual benefit estimates are probabilistically influenced by social opinion. Social opinion is spread via discussions, which are modeled as message exchanges about the social value and the information state. Discussions are triggered by messages from the media that reach individuals at random, with a given frequency. Both initial social value and initial individual benefit are drawn from a normal distribution. Using a small-world type network, the authors experiment with varying initial distributions of social opinion and individual benefit as well as varying average size of the individual's social network and the frequency of mass media messages. Results suggest that innovations with high social value and low individual benefit have a greater chance of succeeding than innovations with low social value and high individual benefit. Extremists with very definite opinions can polarize the social value and strongly affect adoption when the density of the social network and the frequency of discussion are high.

The results of the reviewed studies unequivocally suggest that managers planning the market introduction of an innovation should heed the common wisdom that warns of the destructive power of negative WoM.

3.4.5. Dynamic social networks

Real-world social networks, unlike their idealized representations in most diffusion models, are typically not static, but evolve over time. This may not be relevant if the speed of diffusion is faster than changes in the social network structure and the structure of the social network is not influenced by the innovation itself, but it may be highly relevant for certain types of innovations. In a policy-oriented study, Deroïan (2002) therefore model the social network as a set of relationships generated by the agents themselves. The authors thereby endogenize the evolution of the social network as a step-by-step process based on the assumption that two individuals are more confident in each other if they share a common opinion (i.e., homophily). The simulation captures the emergence of a collective evaluation of an innovation, and explains diffusion failure as the formation of a negative collective evaluation. Unlike most other models reviewed, Deroïan uses a directed influence graph that incorporates both positive and negative (inhibitive) influence. Drawing on ideas from the opinion dynamics literature, the authors model adoption decisions based on individual opinions (i.e., continuous propensities to adopt). The formation of these opinions, as a cumulative process, gradually increases the pressure of the whole community on individual opinions. The authors examine the impact of receptivity and network size on opinion and diffusion dynamics. Results confirm that the diffusion of an innovation can be affected by the state of the influence network in the demand side and that irreversible dynamics occur in the system.

3.4.6. Effectiveness of promotional strategies

ABMs of innovation diffusion offer the potential to explicitly incorporate marketing variables, thus allowing decision-makers to compare different scenarios and test various strategies in what-if experiments. Remarkably, theoretical models have so far largely neglected marketing variables such as product (e.g., product attributes), pricing, and distribution (exceptions that include pricing and changing product designs are outlined in Subsection 3.4.7). Promotion is by far the most widely studied marketing variable in the agent-based innovation diffusion literature.

Using a cellular automaton model (cf. Subsection 3.4.2 for a brief model description), Goldenberg et al. (2001) compare the effect of marketing efforts, weak-tie and strong-tie WoM. Results clearly indicate that beyond a relatively early stage of the diffusion process, the effect of external marketing efforts (e.g., advertising) quickly diminishes and strong and weak ties become the main forces propelling adoption. These results support Rogers' (2003) argument that advertising may be effective in the initial stages of information dissemination, but its importance diminishes after product takeoff and WoM becomes the main mechanism that drives adoption.

Considering both positive WoM from opinion leaders and negative WoM from resistance leaders, Moldovan and Goldenberg (2004) also investigate the effectiveness of advertising (cf. Subsection 3.4.4 for a brief model description). They find that in markets in which both opinion and resistance leaders play a role, advertising has a small and nonlinear effect on market size. According to their results, advertising may decrease market size at high levels, since it activates the market's resistance leaders, who (like opinion leaders) are assumed to be highly attentive to advertising and well connected. Based on this finding, the authors also show that activation of opinion leaders in advance of unfocused advertising messages may mitigate the destructive effect of resistance leaders and increase market size significantly.

Alkemade and Castaldi (2005) investigate whether firms can learn about the network structure and consumer characteristics when only limited information is available, and use this information to evolve a successful directed-advertising strategy. The authors focus on fashionable products and model both "exposure" and "over-exposure" thresholds. Firms are boundedly rational and not fully aware of the structure of the communication channels among consumers. A genetic algorithm is used to identify efficient strategies to target individual consumers and model the strategy search and learning behavior of the firm. Scenarios with varying assumptions about whether consumers may decide to use the product again after discontinuing its use are tested. As expected, results exhibit either oscillating behavior or a permanent negative effect that causes the diffusion to "die off". The authors compare diffusion results obtained with a dynamic advertising strategy (adapted after each period) to random advertising results and demonstrate that the evolved directed-advertising strategies outperform random advertising.

Studying advertising strategies in the context of positive and negative WoM in small-world-type networks, Goldenberg et al. (2007) compare linear and concave advertising strategies (cf. Subsection 3.4.4 for a brief model description). Findings indicate that the optimal level of advertising is affected strongly by the WoM process. In line with Moldovan and Goldenberg (2004), the authors find that too much advertising might indeed negatively affect profitability because although it increases the number of adopters, it indirectly also increases the number of disappointed customers and thus triggers an earlier start of the negative WoM process.

Delre et al. (2007a) investigate how promotional strategies affect the diffusion of new products in terms of final market penetration and time to takeoff. They specify "external marketing effort" as a probability for any non-adopter agent to be convinced to adopt each period and compare multiple timing strategies and two targeting strategies: targeting many small groups in distant places ("throwing gravel") and targeting a small number of large groups ("throwing rocks"). These strategies are tested in brown goods (i.e., electronics) and white goods markets (i.e., household products). Findings indicate that (i) the absence of promotional support and/or a wrong timing of the promotions may lead to a failure of product diffusion; (ii) the optimal targeting strategy is to address distant, small and cohesive groups of consumers; and (ii) the optimal timing of a promotion differs between durable categories (white goods, such as kitchens and laundry machines, versus brown goods, such as TVs and CD players).

An interesting promotional strategy is to leverage the important role of highly connected individuals (i.e., "hubs" or "opinion leaders") and use it as a marketing instrument. In a pioneering, predominantly conceptual contribution, Valente and Davis (1999) investigate how the diffusion of innovations can be accelerated through opinion leader recruitment. They use homogeneous agents that adopt once 15% of their neighbors have adopted. The formal description of the underlying model is sketchy and the network model used, which randomly allocates seven ties per agent, does not appear to resemble most real-world social network structures very closely. Nevertheless, simulation results demonstrate that diffusion occurs faster when initiated by opinion leaders rather than by random or marginal agents and that targeting opinion leaders may therefore accelerate diffusion.

Similar to Valente and Davis (1999), Delre et al. (2010) also investigate the effectiveness of opinion leader recruitment (cf. Subsection 3.4.2 for an outline of their model). Results suggest that the most important function of highly interconnected hubs is to inform others about the new products, but that their effect on the decision making of consumers can be often overestimated. They also find that in markets in which such hubs do not exist, diffusion is less likely to occur. For such markets, direct-to-consumer advertising could be an alternative strategy to stimulate the spreading of the new product in different areas of the network.

Finally, van Eck et al. (2011) also study the role of opinion leaders, but take into account not only their central network position, but also the influence of personality traits and knowledge among influential consumers. To this end, they extend the model developed by Delre et al. (2007a). Like in the original model, agents' adoption decisions are based on a utility threshold function that includes individual preference and social influence parts. Social pressure, however, is not modeled as a threshold, but rather as a continuum (i.e., if more neighbors adopt the product, normative influence in favor of the product increases). Furthermore, the small-world network used in the original model is replaced with a scale-free network to better account for the central position of opinion leaders. The authors test critical assumptions by means of an online survey on the WoM behavior of children in the context of the diffusion of free Internet games. The empirical data supports the hypotheses that opinion leaders (i) are better at judging product quality, although they do not know more about the product, (ii) are more innovative than followers, (iii) take more central positions in the network, and (iv) are less susceptible to normative influence than followers. The authors parameterize the model accordingly and find significant differences between networks that contain opinion leaders and those that do not. In particular, opinion leaders increase the speed of the spread of information, the adoption process itself, and the maximum adoption percentage. The results indicate that targeting opinion leaders is a valuable marketing strategy not only because of their central position, but also because of their influential power.

Overall, we can conclude that advertising can be an important driver for diffusion success, particularly in the initial stages of information dissemination. Advertising strategies directed at highly connected individuals can be effective in accelerating diffusion. In the presence of negative WoM, however, too much advertising might even have an adverse impact on innovation success. To mitigate the destructive effect of negative WoM, firms should aim to activate opinion leaders in advance. While absence of promotional support may lead to failure of product diffusion, optimal timing and targeting of distant, small, and cohesive groups of consumers may accelerate diffusion. Nevertheless, the most important role of advertising is to spread initial awareness. Adoption itself is mostly driven by WoM, in particular after takeoff, rather than directly being influenced by advertising.

3.4.7. Endogenous innovation, co-evolution, and competitive diffusion

Theoretical models have so far focused on the diffusion of singular innovations and largely neglected competition with existing products or competitive diffusion of multiple innovations. However, there are some notable exceptions that consider multiple exogenously defined or endogenously emerging products.

Goldenberg and Efroni (2001) conceptualize innovation not as an antecedent that precedes diffusion, but rather as a consequence of emerging needs that propagate in the market. The proposed stochastic cellular automaton model incorporates inter-firm competition for the exclusive discovery of emergent "marketing awareness" and estimates a firm's probability of being "first and alone" in the market. The spread of awareness of a need is modeled via two mechanisms: spontaneous, discovery-driven transformation with a fixed probability and WoM induced awareness with a probability which is based on the number of (Moore-) neighbors in the "aware" state. Firms can sample the market to identify new needs. To create the experimental conditions, the authors vary the probabilities for spontaneous and WoM driven adoption as well as the number of firms. Results show that if traditional exploration is applied, there is a high probability that at least one other competitor will discover the same need before, or concurrently with the firm in question. Hence, pioneer status cannot be achieved by exclusive dependence on market-based information. These findings suggest that alternative methods to identify emergent needs based on information that is invariant to market awareness are necessary.

Like Goldenberg and Efroni, Janssen and Jager (2001, 2003) also endogenize innovation, but model market dynamics from a social psychology perspective. In the proposed models, products remain in the market as long as they maintain a minimum level of market share, else they will be replaced by a new product. Agents' decision making is modeled following the "consumat" approach developed by Jager et al. (2000) and agents switch between various cognitive strategies (social comparison, repetition, imitation, deliberation) depending on their level of need satisfaction and their experienced degree of uncertainty. A small-world-type network topology is used in Janssen and Jager (2001), and complemented with experiments with scale-free networks in Janssen and Jager (2003). Results indicate that market dynamics is a self-organized property that emerges from the interaction between agents' decision making process, the product characteristics, and the structure of interactions between agents. The behavioral rules that dominate the artificial consumer's decision making determine the resulting market dynamics, such as fashions, lock-in and unstable renewal.

To analyze the diffusion of green products, Janssen and Jager (2002) formulate a co-evolutionary model in which both consumers and firms are heterogeneous in their behavioral characteristics. Each firm produces one core product which it changes in an evolutionary process if it does not meet its business target, defined as a minimum average profit rate. Firms are assumed to be either innovators or imitators who copy successful competitors. Consumer agents have two needs: a social need and a personal need. Personal need satisfaction depends on the difference between the characteristics of the consumed product and the preferred "ideal" characteristics. It is assumed that social need satisfaction rises linearly with the number of neighbors who consume the same product. The total level of need satisfaction is defined as a weighted sum of personal and social need satisfaction and rescaled by the relative price level. Consumer agents are heterogeneous in their personal preferences regarding product characteristics and weights of personal and social needs. Simulation results suggest that more deliberation, as is usually the case with important consumptive decisions, yields a faster diffusion in a market in which firms do not adapt their products, but a slower and incomplete diffusion in a market in which firms continuously adapt their product designs.

Schramm et al. (2010) model brand level interactions in the diffusion of durable products and define multiple types of agents (innovators, early adopters, late adopters) that differ in their sensitivity to features, price, promotion, and social influence. Individual adoption thresholds are specified as a function of feature, price, promotion and social influence and compared to fixed exogenous adoption thresholds to determinate adoption behavior. The proposed model does not incorporate social networks and only considers global feedback (total proportion of consumer agents that have adopted). Parameters used in the simulation runs are not fully specified in the paper. The authors present simulation results for sample scenarios modeling the digital camera market and conclude that ABM can be applied to improve understanding of the brand and market-level reactions to changes in marketing mix strategy.

3.5. Review of applications and policy analyses

The papers reviewed in the previous section apply ABMs as tools to explore theoretical research questions by means of thought experiments. Rather than predicting the spread of particular innovations at actual markets, these models aim at general insights about diffusion processes on a highly abstract level. Given that ABMs are "much more concerned with theoretical development and explanation than with prediction" (Gilbert, 1997), it is not surprising that the majority of papers reviewed falls into this category.

This notwithstanding, attempts have also been made to demonstrate the methodology's potential as a practical tool for tackling real-world problems. As ABMs mature, the number of contributions that adopt an applied perspective and aim at providing decision-makers with forecasts, management diagnostics, policy analyses and decision support is increasing rapidly. In this section, we review the still limited, but growing body of applied literature. Table 3.4 provides an overview of the reviewed papers and their application domain. We structure our review around the major substantive domains in which studies have been conducted so far, each of which is typically based on empirical microdata from a particular geographic region.

3.5.1. Agriculture

Rural sociology is the research tradition credited with forming the basic paradigm for diffusion research. According to Rogers (2003), it has produced the largest number of diffusion studies so far. By that standard, the number of ABMs concerned specifically with agricultural innovations is still small; only two of the reviewed papers fall into this category.

Berger (2001), simulates the diffusion of agricultural innovations and water resource use in Chile and assesses policy options in the context of resource use changes and the Mercosur agreement. In light of scarce aggregate agronomic data in transition and developing countries, the authors motivate the agent-based approach with its ability to make use of rich available microdata (e.g., from experimental stations, farm records, sample surveys, experts' opinions, and direct observations on field trips), to account for technical, financial, and behavioral constraints at the farm level, to capture a rich set of interactions, and to explicitly model space. The model

Code	Reference	Application domain
A1	Berger (2001)	agricultural innovations
A2	Broekhuizen et al. (2011)	cinema market
A3	Dugundji and Gulyás (2008)	transportation mode alternatives
A4	Faber et al. (2010)	micro-cogeneration of electricity
A5	Gallego and Dunn (2010)	healthcare provisioning
A6	Günther et al. (2010)	alternative fuels
A7	Kaufmann et al. (2009)	organic framing practices
A8	Kim et al. (2011)	automobile market
A10	Schwarz and Ernst (2009)	water saving innovations
A11	Schwoon (2006)	fuel cell vehicles
A12	Vag (2007)	mobile phones
A13	van Vliet et al. (2010)	alternative fuels
A14	Zhang and Nuttall (2011)	smart metering
A15	Zhang et al. (2011)	alternative fuel vehicles

Table 3.4.: Applications and policy analyses reviewed

consists of an economic and a hydrologic component bound into a spatial framework; agents represent farms that interact in various ways, including contagion of information, exchange of land and water resources, and return-flows of irrigation water. The authors identify likely diffusion patterns for specific agricultural innovations and also investigate expected consequences in terms of changes in the use of water, farm incomes, and structural effects of the innovation processes.

Kaufmann et al. (2009) study the diffusion of organic practices through farming populations in Latvia and Estonia and evaluate the effectiveness of policies to promote them. In particular, they model the effect of social influence, introduction of a higher subsidy, and increased support by organic farm advisors. Based on theory of planned behavior, farm agents exchange opinions, update subjective norm estimates, and adopt organic farming practices if intention exceeds an empirically derived threshold. The authors use a survey dataset collected from regions in Latvia and Estonia and model the complete population of organic and conventional farmers in both countries. Results suggest that social influence alone makes little difference and that economic factors (e.g., introduction of a subsidy) are more influential. However, the combined adoption rate from social and economic influences is higher than the sum of the proportion of adopters resulting from just social influence and from just subsidies. The authors derive specific policy recommendations for both countries and conclude that policies are more effective if they are sensitive to the specific contexts.

3.5.2. Energy, transportation, and environmental innovations

Judging by the number of agent-based studies in this area, environmental innovations appear to be of particular concern to innovation diffusion researchers. This may on the one hand be attributed to their societal relevance, and on the other hand to a number of aspects that call for an individual-based approach, such as the high relevance of social influence as well as varying consumer preferences and attitudes toward "green innovations". Zhang et al. (2011) also argue that environmental innovations do not follow the prototypical Bass diffusion curve because of long take-off times and diffusion discontinuities.

Several authors have looked into alternative transportation modes and alternative energy sources for transportation. Simulating the diffusion of fuel cell vehicles, Schwoon (2006) study the impact of governmental policies and public infrastructure build-up programs. Consumers' behavior is modeled by means of the "consumat" approach (cf. Jager et al., 2000). Findings indicate that a reasonable tax on conventional cars would be sufficient to overcome the "chicken and egg problem" of car producers not offering fuel cell vehicles as long as there are no hydrogen filling stations, and infrastructure not being set up unless there is a significant number of fuel-cell vehicles on the road.

Zhang et al. (2011) investigate factors that can speed the diffusion of hybrid and electric vehicles on the U.S. market. They model the relationship between multiple agents with unique objectives: (i) consumers, who maximize utility and minimize cost, (ii) manufacturers, who maximize profits, and (iii) governmental agencies, that maximize social benefits. Manufacturer agents optimize their products by means of simulated annealing. Consumer agents choose any or none of the available vehicles to buy. All consumer agents are assumed to be affected by WoM and domain-specific knowledge in the same way and they are not embedded in an explicit social network. Consumers' decision making is grounded in empirical choice-based conjoint data, i.e., each consumer agent is initialized with individual preferences (with respect to vehicle design, fuel type, miles per gallon, miles between charge, and price) corresponding to an individual respondent in a panel survey of automobile experts (the authors acknowledge that the sample population is favorably biased toward alternative fuel vehicles). the authors compare the impact of three mechanisms: an alternative fuel vehicle mandate (i.e., technology push), WoM (i.e., market pull), and fuel economy mandates (i.e., regulatory push). Unsurprisingly, mandating manufacturers to produce only hybrid and electric vehicles is found to speed diffusion of these types of vehicles, in particular that of hybrid options. WoM also positively affects diffusion by decreasing the preference for fuel-inefficient vehicles and inducing a higher willingness to pay for alternative fuel vehicles. Perhaps most interestingly, the authors find that fuel economy mandates (i.e., any vehicle that does not achieve at least 27.5 miles per gallon must pay a penalty) lead to an increase in the market share of fuel-inefficient vehicles and therefore increases air pollution. This counter-intuitive finding results from consumers willingness to pay the higher prices (due to penalties passed on by the manufacturers) in order to buy SUVs (including hybrid). The authors conclude that both society and individual consumers are negatively impacted by policies that impose fees that can be re-directed toward the retail price of a vehicle. Results also indicate that there is little interest in electric vehicles and that price will have to decrease and miles between charges have to increase significantly for this type of vehicle to reach the mainstream market. Methodologically, the study demonstrates how a thorough verification and validation of agent-based diffusion models can be achieved by grounding, calibrating, verifying, and harmonizing the model.

Günther et al. (2010) simulate the diffusion of a second-generation biomass fuel on the Austrian market. In the proposed model, fuels are characterized by the attributes price, quality, and "expected environmental friendlyness". Consumers' adoption decisions are modeled by means of heterogeneous information and utility thresholds; agents adopt once they have obtained sufficient information (from other consumer agents or through promotional activities) and the utility of the biomass fuel exceeds their adoption threshold. Consumers spread information in a "preference-based" network in which links are created based on geographic distance and agents' consumer type. Homophily is assumed, i.e., agents of the same type are more likely to be connected. In their simulation experiments, the authors divide the market into four segments (price-sensitive, quality-seeking, "eco-consumers" and "snob buyers") and set agents' preference weights accordingly. They conduct experiments to compare the effectiveness of promotional timing (continuous vs. intermittent) and targeting (experts, consumers in different regions) strategies and combine them with one of two dynamic pricing strategies (skimming vs. penetration). Results indicate that directing promotional activities at opinion leaders can accelerate diffusion considerably. Furthermore, results clearly indicate that speed and success of diffusion is dependent on the geographic area targeted (e.g., large vs. small cities).

A different model that is also concerned with the adoption of transportation fuels is put forth by van Vliet et al. (2010). They examine the impact of marketing activities and governmental policies on the diffusion of various conventional fuels and fuel blends (produced by means of 13 different production chains). In their model, fuels are characterized by four attributes: driving costs, environment, performance, and reputation. The authors assume lexicographic preferences; in particular, they assume that price is most important and that other attributes only play a role if prices are similar. The authors define eleven consumer types on the basis of socio-demographic data. Experiments with policies such as price reductions (e.g., through tax and import tariff reductions), perceived emission reductions (through a successful large scale sustainable biomass certification scheme), and addition of a "buzz-factor" that increases perceived market share reveal that sustained combinations of interventions are required to bring about a transition away from petrol or diesel. Results suggest that adoption of alternative fuels is likely confined to niche markets with a share of 5% or lower.

Motivated by traffic congestion problems in the Netherlands, Dugundji and Gulyás (2008) study the effects of household heterogeneity and their interactions in the adoption of various transportation mode alternatives. Their approach starts out with classic econometric methods (multilevel nested logit model), but combines the static estimation model with agent-based methods to simulate the evolution of choice behavior over time. Assuming that each agent's choice (which represents that of multiple households) is directly influenced by the choices of its neighbors and socioeconomic peers that make each choice, interactions are modeled in both social and spatial network structures. Simulation results of a multinomial logit formulation of the model indicate that there is a unique emergent equilibrium solution with a mode share of 60% for automobile commuters, approximately 25% for public transit, and approximately 15% for bicycle commuters. Simulation results of a nested logit version, however, are dramatically different with a mode share of approximately 93% for public transit commuters. The paper presents a promising methodological approach for combining agent-based modeling with econometric estimation, which allows researchers to make use of empirical microdata. However, counter-intuitive and inconsistent results do not allow to draw any practical conclusions for the application case at hand. Furthermore, because the model does not focus on innovations, the approach cannot be applied directly to cases where consumers are not aware of the full set of available alternatives.

The models discussed so far in this section aim for predictive accuracy. However, due to the inherent problem that innovation diffusion predictions can only be validated ex-post, all of them are, at least to some extent, speculative thought experiments until data for validation becomes available. One of only a few ABMs that demonstrably replicate observed market behavior is put forth by Kim et al. (2011), who model diffusion in a competitive automobile market. In the proposed model, consumers evaluate available cars characterized by multiple cost and benefit attributes based on available product information, their individual preferences, and social influence. An innovative aspect of their approach is the use of multi-attribute fuzzy decision making. The authors simulate the diffusion of six full-sized cars available in the Korean market. To obtain data for model parameterization, they conduct a survey with 400 potential consumers to estimate their individual weights for nine attributes as well as sensitivity to social influence. Calibrating the small world social network parameters with observed diffusion data, the authors find that the simulated results fit actual sales data well. The approach for model calibration and ex-post validation is interesting and initial results appear promising. It would be even more intriguing to examine whether the calibrated model is also capable of producing ex-ante estimates of the diffusion of newly introduced cars, rather than replicating past observed diffusion when calibrated appropriately.

Apart from alternative transportation modes and energy sources, innovations that may reduce domestic water and energy consumption have also garned recent interest. In the remainder of this section, we review three models that evaluate government policies to promote such innovations.

The first, Schwarz and Ernst (2009), is concerned with the diffusion of water-saving innovations in Southern Germany. In the proposed model, each agent represents the households of one of five “lifestyle groups” on one square kilometer. The definition of these lifestyle groups (“Sinus-Milieus”) is not specified in the paper. Agents decide upon adoption or rejection of shower-heads, toilet flushes, and a rain-harvesting system. Depending on the innovation category and lifestyle group, one of two decision rules is used to make adoption decisions: (1) a cognitively demanding deliberate decision rule, which is based on multi-attribute utility functions, or (2) a simple rule based on a lexicographic heuristic and imitation. The authors use empirical data from a questionnaire survey and validate the model with historic marketing data on toilet flush adoption. Simulation results suggest that water-saving innovations are likely to diffuse further in Southern Germany and that therefore, water demand per capita is bound to further decrease if water-related habitual behavior remains more or less constant.

Faber et al. (2010) model the adoption of domestic micro co-heating and power (micro-CHP) in the Netherlands, which produces electricity in co-generation with domestic heating. Assuming falling prices due to learning effects, they examine whether subsidy schemes can effectively accelerate the diffusion of micro-CHP. In the proposed model, agents are perfectly rational and make decisions to buy conventional condensing boilers or adopt micro-CHP based on total upfront and usage cost. The authors account for heterogeneity by modeling five house types with corresponding levels of natural gas needed for domestic heating, but do not model any interactions between agents. The proposed model is therefore a micro-model, but lacks important characteristics of ABMs, which is why no emergent phenomena can be expected in the results. Publicly available empirical data from various sources as well as estimates for gas and electricity use for the five housing types modeled are used in the simulations. Not surprisingly, the authors find that the market diffusion of micro-CHP is affected significantly by fuel prices. In particular, results show that the effect of electricity price considerably offsets the effect of gas price. Based on simulations of various subsidy schemes that affect either cost of purchase or costs for usage, they also conclude that subsidies could considerably accelerate the diffusion of micro-CHP.

Finally, Zhang and Nuttall (2011) introduce a model that simulates the diffusion of smart electricity meters (a technology that offers consumers detailed information about energy consumption) in Great Britain as a function of different policy options. Consumers’ decision making is formalized using theory of planned behavior. More precisely, consumer agents’ attitude is expressed as a function of electricity prices and individual price sensitivity. Their subjective norm toward choosing an option is influenced by WoM and the agent’s individual motivation to comply. Perceived behavioral control is influenced by a range of environmental factors such as smart metering infrastructure or service availability. Combining these factors, a consumer agent’s intention to choose an option is formalized as a function of it’s attitude, subjective norm, and perceived behavioral control toward choosing an option. Electricity supplier agents adjust electricity prices once every three months and disseminate price information to consumer agents. The environment is modeled as a square lattice with periodic boundary conditions. Consumer agents are linked to neighboring agents as well as to random remote agents. The authors note that the resulting interaction structure exhibits both small-world and scale-free characteristics. Four scenarios are evaluated, varying who pays for the smart meters (government, electricity suppliers, or distribution network operators) and how they are rolled out (competitively or monopoly). Adoption is fastest in the government-financed competitive roll-out scenario, followed by government-financed monopoly roll-out and electricity supplier-financed competitive roll-out. After the introduction of smart meters, the simulation shows a dynamically unstable state of consumer switching. As a policy implication, the authors suggest that the U.K. government, in mandating electricity supplier-financed competitive roll-out, is currently pursuing the least effective strategy because electricity suppliers tend to avoid using any mass media to disseminate the policy since they have to bear the cost of the meters.

3.5.3. Miscellaneous domains

In recent years, the spectrum of substantive domains in which pioneering applications of agent-based diffusion models have been developed has grown rapidly. To forecast future preferences, Vag (2007) develops a dynamic conjoint model that simulates changes in consumers' individual product priorities and presents an application to the mobile phones market. Unfortunately, the author does not provide a formal specification of the model. The results presented are highly sensitive to chosen parameters and appear highly path dependent and unstable. The author does not discuss managerial implications.

Studying the diffusion of medical practices in healthcare systems, Gallego and Dunn (2010) identify how innovation diffusion processes may lead to inequality of overall levels of recommended care. Using empirical network data from Australia, they simulate the diffusion of medical practices through a population of clinicians and find that stronger clustering within hospitals or geo-political regions is associated with slower adoption amongst smaller and rural facilities.

An application to the motion picture market is put forth by Broekhuizen et al. (2011). Using an ABM, they show that cross-cultural differences in social influence cause market inequalities and validate these results with survey data from China, the Netherlands, Italy, and Spain. The ABM they develop mimics the behavior of movie visitors and incorporates the social influences they exert on each other before and after visiting movies. This explicit distinction between the effects of coordinated consumption (i.e., social influence derived from intended behavior of others) and imitation (i.e., social influence derived from the past behavior of others) is a unique contribution of their paper. The model can be summarized as follows: Each simulation period, consumer agents become aware of movies with a probability determined by the buzz these movies create, which before release depends on pre-release advertising budget and after release depends on success at the box office. Then, agents are selected according to their heterogeneous probabilities of attending a movie. For each agent, expected utility, which is specified as the sum of individual and social utility parts, is calculated for each movie it is aware of. Individual utility is based on the fit between individual preferences and the movie characteristics; social utility is based on the fraction of agents that have seen the movie (imitation), and the proportion of agents that are informed about the movie but have not seen it yet (coordinated consumption). Hence, social influence is modeled on the macro-level and no social network is used to structure interactions. The main simulation results provide an explanation why a few movies dominate the market and show that social influence is the main driver of market inequalities. Furthermore, results indicate that coordinated consumption has a much stronger effect (almost four times) than imitation. The authors confirm this result empirically by means of a cross-national field study in countries selected based on their level of individualism (vs. collectivism). Results suggests a U-shaped relationship between a country's level of collectivism-individualism and members' susceptibility to social influence. Apart from the explicit distinction between pre- and post-purchase WoM as an important theoretical contribution, and the generated insights about cultural differences in the motion picture industry, the paper also contributes methodologically by demonstrating how agent-based modeling and empirical surveys can complement each other to create new insights that could not be gained using either method alone.

We can conclude that even though agent-based diffusion models are still in their infancy, they have already created intriguing new research opportunities by facilitating a transition from an aggregate-level to an individual-level perspective. In particular, agent-based modeling has improved our understanding of innovation diffusion and has been applied to investigate a number of specific real-world cases.

4. Model Design

Building on a thorough review of existing agent-based models of innovation diffusion in the previous chapter, which revealed a number of research gaps, this chapter proceeds to develop a spatially explicit model of innovation diffusion that accounts for competitive interaction and covers all stages of the innovation-decision process. To this end, it first defines objectives for the modeling endeavour in Section 4.1, outlines the strategy for modeling time and space in Section 4.2, and develops the formal model in Section 4.3 and Section 4.4.

4.1. Modeling objectives

Versatility The main goal in the development of the model introduced in this thesis is to bridge the gap between highly abstract theoretic models on the one hand, and very specific models for particular applications on the other hand.

As the review in the previous chapter has shown, theory-building models are frequently based on very simple (if not simplistic) conceptions of human decision making. These models do not aim to provide forecasts or support real-world decisions and the quantitative results they produce should therefore only be interpreted qualitatively with respect to the modeled effects. More recently, this role of ABMs in diffusion research as tools for theoretical inquiry has been complemented by ABMs tailored to particular application domains. The latter models provide managerial guidance and policy analyses, but they are not generic enough for being used in any other than the narrow substantive domains they are designed for.

The gap between these two extremes is an area in which progress would be highly beneficial in terms of providing managers with simple, robust, adaptive and easy to control models that are as complete as possible (cf. Little, 1970) and still applicable to a range of applications as wide as possible. So far, models have not been designed to be used by and support end-users directly, which may be attributed to their relatively early stage of development. To make progress towards providing decision support, an adaptable and versatile model needs to be developed.

Balancing of abstraction and descriptiveness Theoretic models (reviewed in Section 3.4) have so far largely avoided the incorporation of sophisticated decision rules based on the evaluation of multiple attributes and intentionally modeled agents' behavior in a highly stylized manner. These models have primarily followed the postulation that complexity should be in the results and not in the assumptions of the model (cf. Axelrod, 2007). However, this approach comes with the risk of missing important aspects of the modeled real-world behavior and, thus, ending up with an inadequate model. The model developed in this thesis primarily aims at supporting decisions rather than contributing general theoretical insights about market mechanisms. For these purposes, crude and highly stylized modeling of decision mechanisms is insufficient, and we therefore aim for a more detailed, multi-attribute model of consumer decision making.

At the same time, it is necessary to keep in mind that excessively detailed modeling on the micro-level may lead to an over-specified model that includes a lot of complexity on the micro-level and is difficult to parameterize with empirical data.

A critical challenge in the development of this model therefore lies in striking an appropriate balance between aiming for a simple model ("keep it simple stupid") that may be enriched later on, and aiming for a highly descriptive model ("keep it descriptive stupid") that can be simplified wherever justified (cf. Edmonds and Moss, 2006, who discuss this issue in detail and favor the latter approach). The main rule we use for seeking this balance and deciding whether or not to include an aspect into the model is to ask whether it contributes to making the model more capable of supporting managerial decisions.

Spatial explicitness Innovation diffusion has long been recognized and modeled as a spatial process in the geographic research community, starting with seminal empirical work and early simulation models by Hägerstrand (1967), which clearly demonstrated the important role of spatial distance in the person-to-person diffusion of an innovation (Brown, 1981; Rogers, 1983). In sociological research, the relevance of space in the diffusion of innovations is also generally accepted, as illustrated by the Strang and Soule's 1998 remark that *"perhaps the most common finding in diffusion research is that spatially proximate actors influence each other."* Mahajan et al. (1990, p. 21) also advocate the integration of the temporal and spatial dimensions of diffusion. However, after the seminal work by Hägerstrand, few efforts were made to capture space in mathematical models of innovation diffusion. Rogers (1983, p. 268), who also stresses the importance of what he calls "neighborhood effects", concluded that *"space is probably one of the least studied variables in the diffusion process"*.

A likely reason for this lack of research is that aggregate diffusion offer only limited potential to consider the spatial dimension and have largely been limited to investigations at the macro-scale of analysis (for studies of the global diffusion of innovations, for example, cf., Putsis et al., 1997; Dekimpe et al., 2000; Tellis et al., 2003). Disaggregate models of innovation diffusion, by contrast, offer a rich potential to study spatial diffusion since they can easily account for spatial heterogeneity on the micro-level.

As the literature review in Chapter 3 revealed, however, space has been largely neglected in the ABMs developed so far, some notable exceptions in the applied literature (Gallego and Dunn, 2010; Günther et al., 2010; Schwarz and Ernst, 2009) notwithstanding. Although the cellular automata models that appeared in the literature (e.g., Cantono and Silverberg, 2009; Goldenberg and Efroni, 2001; Goldenberg et al., 2001, 2007, 2010a; Hohnisch et al., 2008; Kocsis and Kun, 2008; Martins et al., 2009) are based on various forms of two-dimensional square lattices (with or without periodic boundary conditions; with Moore or von Neumann neighborhoods, with or without rewiring etc.), it is often unclear how their discrete and regular spatial structure relates to real space. Typically, it relates more to an abstract relational space rather than an actual geographic space in which actors are distributed continuously, irregularly, and heterogeneously.

To account for this finding and allow analysts to evaluate rollout strategies spatially, we chose to embed consumer agents as well as points of sale in continuous space.

Comprehensive modeling of the innovation-decision process Diffusion theory suggests that consumers undergo various stages when accepting and adopting an innovation. Rogers (2003, p. 169) distinguishes five stages of the innovation-decision process: (i) *knowledge* occurs when an individual is exposed to an innovation's existence and gains an understanding of how it functions (ii) *persuasion* occurs when an individual forms a favorable or unfavorable attitude towards the innovation (iii) *decision* takes place when an individual engages in activities that lead to a choice to adopt or reject the innovation (iv) *implementation* occurs when an individual puts a new idea into use, and (v) *confirmation* takes place when an individual seeks reinforcement of an innovation-decision already made, but he or she may reverse this previous decision if exposed to conflicting messages about the innovation.

For the most part, diffusion models have so far characterized the first four stages, with implementation representing first purchases (Parker, 1994). The persuasion stage is frequently modeled only rudimentarily and the formation of attitudes towards an innovation is typically not captured in aggregate models. In most of the existing agent-based models, the confirmation stage is also not considered explicitly (cf. the review in Chapter 3). The reason for this is that virtually all diffusion models are exclusively concerned with initial adoption (i.e., first purchases) of consumer durables. For these products, the relevance of repeat purchase decisions may be neglected during their initial introduction, even though confirmation may significantly affect WoM behavior.

In the diffusion of many frequently purchased products, however, repeat purchase may have a significant impact because consumers can use information from post-purchase evaluation in their repeat purchase decision and WoM referral behavior. For these products, repeat purchases may hence act as a social signal and accelerate the diffusion of (positive or negative) word of mouth about the product.

ABMs that account for repeat purchase could improve our understanding of how initial adoption and repeat purchases jointly shape diffusion processes. Repeat purchases should also not be neglected for practical reasons, since they are a major source of revenue in many goods and services industries (Peres et al., 2010) and determine firms' long-term growth and profitability.

Developing agent-based model for sales, rather than strictly limiting the analysis on initial adoption, is therefore a promising field in diffusion modeling (Peres et al., 2010; Delre et al., 2010). In the development of the current model, we aim to incorporate trial and repeat purchase decisions and to model all stages of the innovation-decision process. Figure 4.1 illustrates Rogers' innovation-decision process and provides a mapping of elements of the proposed model to the individual stages.

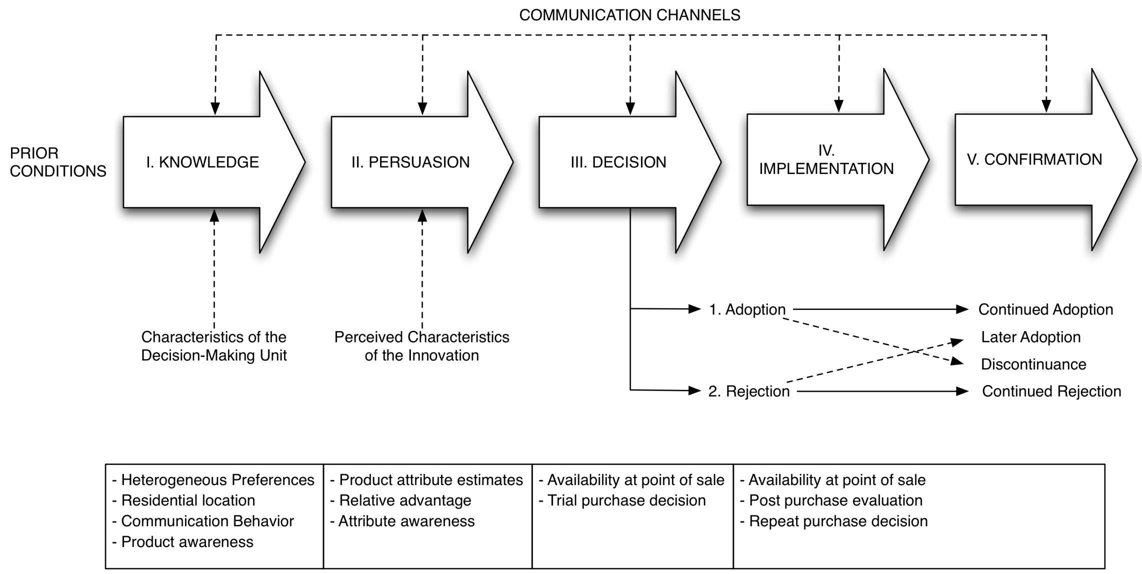


Figure 4.1.: Innovation-decision process and mapping of model elements to the individual stages (Source: adapted from Rogers, 2003, p. 170).

Modeling of competitive interaction Most existing diffusion models are based on the assumption that the innovation has its own exclusive market potential, which is not affected by competitors' products or actions. More often than not, however, firms face intense competition from incumbent products and/or other innovations when introducing new products.

Some market dynamics models proposed in the literature (Janssen and Jager, 2001, 2002, 2003) capture competition on an abstract level and simulate market dynamics based on detailed psychological models of consumer behavior. Buchta et al. (2003) model competition between an incumbent and an entrant to study the emergence of disruption but do not focus on diffusion processes. In the current model, we aim to account for consumer behavior in a competitive multi-brand context in order to realistically capture market dynamics and obtain insights into their effects as well as to provide managers with decision support in a competitive setting.

Incorporation of multi-attribute consumer decision-making To make progress towards models that account for competition, it is necessary to develop appropriate methods to capture product characteristics and consumer preferences. Early attempts in this direction have been made in applied diffusion models tailored to specific applications (Schwoon, 2006; Schwarz and Ernst, 2009; Günther et al., 2010; van Vliet et al., 2010; Kim et al., 2011; Zhang et al., 2011).

In the current thesis, our aim is to incorporate a versatile formulation of multi-attribute consumer decision-making and to illustrate how conjoint methods can be used to elicit consumer preferences for the parameterization of agent-based models that incorporate multiple product attributes.

4.2. Modeling strategy

4.2.1. Modeling of time

Timing is critical in agent-based models, because the way time is handled may affect model behavior and simulation results and lead to phenomena that do not follow from deliberate modeling assumptions and decisions, but are methodological artifacts of the particular choice for the modeling of time. Modelers should therefore have good reasons for choosing one method for handling time over another (Radax and Rengs, 2010). Figure 4.2 provides an overview of available approaches.

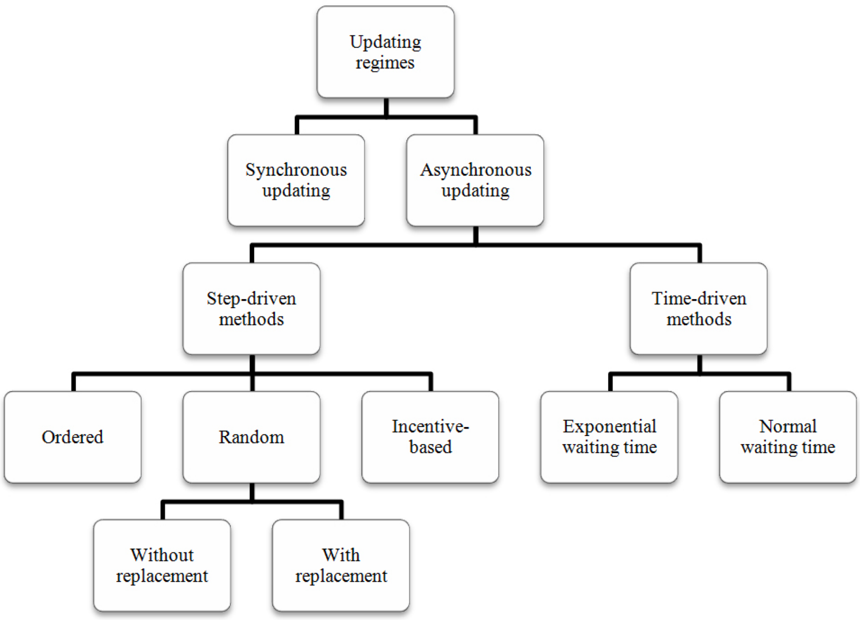


Figure 4.2.: Overview of updating regimes (Source: Radax and Rengs, 2010)

ABMs proposed in the literature so far have typically followed a discrete time approach, dividing time into a series of simulation periods. By doing so, they impose a specific temporal

Synchronous updating	Asynchronous updating
Goldenberg and Efroni (2001)	Kocsis and Kun (2008)
Goldenberg et al. (2001)	Martins et al. (2009)
Deroïan (2002)	Faber et al. (2010)
Maienhofer and Finholt (2002)	
Delre et al. (2007a)	
Vag (2007)	
Hohnisch et al. (2008)	
Cantono and Silverberg (2009)	
Schwarz and Ernst (2009)	
Choi et al. (2010)	
Gallego and Dunn (2010)	
van Vliet et al. (2010)	
Broekhuizen et al. (2011)	

Table 4.1.: Updating in agent-based models of innovation diffusion

structure on the interactions in the model and it typically becomes necessary to define the order in which agents should act. This issue arises not only in agent-based, but also in classic cellular automata models, which usually follow discrete time approaches as well. In the cellular automata literature, it has long been recognized that many phenomena discovered are a mere artifact of the particular way time is handled in the model. In the ABM community, by contrast, this issue has been given little attention so far (with the notable exceptions of Axtell, 2001; Radax and Rengs, 2010).

The most common updating method in cellular automata models is synchronous updating (Radax and Rengs, 2010). When this regime is applied, state changes of cells (or agents) are a function of the state of the automaton in the previous period. All cells (or agents) are tied to the same external clock that synchronizes their actions. As the overview in Table 4.1 shows, the synchronous updating method is also very common in agent-based models of innovation diffusion, some of which exhibit strong traits of the cellular automaton modeling paradigm. In social processes, however, there typically is no natural external clock that triggers synchronous events and the particular way of organizing time in a discrete, synchronous manner therefore imposes artificial structure on the social process for which there is frequently no natural equivalent.

Asynchronous updating, by contrast, is based on the idea of updating one cell (or agent) at a time and holding the rest of the system constant until the update is completed. As illustrated in Figure 4.2, step-driven approaches to do so, which also divide time into discrete periods, are based on the idea of repeating this procedure period after period for each agent, either in an ordered sequence, by randomly picking agents with or without replacement, or by choosing the agent with the highest incentive to become active based on a definition of utility gain from activation (cf. Page, 1997). Asynchronous methods are much less common in agent-based diffusion models, as can be seen from Table 4.1. It has to be noted, however, that the largest group is that of models for which the updating regime is not clearly specified in the publications describing them.

To the best of this author's knowledge, the proposed model is the first agent-based diffusion model to employ a continuous time (i.e., asynchronous and time-driven) mechanism. The main advantage of this approach is that it simulates the diffusion process in continuous time and hence does not impose an artificial structure on interactions. It also fits the agent-based paradigm well on a conceptual level. Agent-based modeling is fundamentally based on the idea that emergent outcomes on the macro-level result from interactions between autonomous entities on the micro-level. Discrete time methods, however, transfer control over the timing of events to some centralized mechanism and thereby limit agents' autonomy to decide when to become active themselves. Time-driven methods, by contrast, enable modelers to let distributed agents schedule events autonomously, an approach that is closer in line with the disaggregate and decentralized agent-based modeling paradigm. Schönfisch and de Roos (1999) make a similar argument in a cellular automaton modeling context by noting that time-driven methods are "the most satisfying from a theoretical point of view"[1]. Within time-driven methods, Radax and Rengs (2010) distinguish between exponential and normal waiting time methods. In both cases, events are scheduled in continuous time, which is represented as a real-valued variable t (rather than an integer-valued "period counter" t). The simulation maintains an ordered list of events that are executed sequentially at the time they are scheduled. The continuous modeling of time eliminates the issue of agent activation and the need to define an artificial sequence of events within periods. In the proposed model, every agent has its own "clock" (i.e., stochastic arrival processes) for scheduling events. While exponential or normal waiting times can be used as a reasonable default assumption, the model allows more generally for arbitrary waiting time distributions for the various types of events in the model.

4.2.2. Modeling of space

In a spatial model, entities can either be associated with a geometric location in continuous space or be restricted to a discrete, grid-based geography. The latter approach is common practice in cellular automata models, where a two-dimensional grid is often used as a pseudo-spatial structure that does not necessarily relate to geographic space.

In the proposed model, agents are embedded in a geospatial environment in continuous space. Consumer agents and points of sale are distributed in geographic space. Space is also taken into account in the construction of the social network.

[1] They refer specifically to exponential waiting time methods, but their argument holds more generally.

4.3. Model entities

Having defined modeling objectives and outlining the strategy for modeling space and time, we can now turn to the development of the formal model by specifying its entities.

4.3.1. Products

To account for multiple products, we define a set P of m products indexed by $i = 1, \ldots, m$. The products are characterized by a set of n attributes indexed by $j = 1, \ldots, n$.

To characterize products along multiple dimensions, let $v_{i,j}^{true}$ be a real number that describes the performance of product P_i with respect to attribute A_j on an interval or ratio scale. These attribute values are assumed to be constant over the simulation time. All products' attribute values can be represented as a matrix $V = (v_{i,j}^{true})_{m \times n}$, i.e.,

$$V_{m,n} = \begin{array}{c} \\ P_1 \\ P_2 \\ \vdots \\ P_n \end{array} \begin{array}{c} \begin{array}{cccc} A_1 & A_2 & \cdots & A_n \end{array} \\ \begin{pmatrix} v_{1,1}^{true} & v_{1,2}^{true} & \cdots & v_{1,n}^{true} \\ v_{2,1}^{true} & v_{2,2}^{true} & \cdots & v_{2,n}^{true} \\ \vdots & \vdots & \ddots & \vdots \\ v_{m,1}^{true} & v_{m,2}^{true} & \cdots & v_{m,n}^{true} \end{pmatrix} \end{array}, \tag{4.1}$$

that contains the "true" attribute values $v_{i,j}^{true}$ for each product i and attribute j.

In line with the diffusion of innovations paradigm, an important feature of the proposed model is that consumers do not generally have perfect knowledge of available products' characteristics and therefore do not necessarily know the "true" attributed values. Instead, they estimate product attribute values based on limited local information obtained from (i) peers in their social networks, (ii) promotional activities, such as mass media campaigns or targeted advertising, and (iii) post-purchase evaluation after initial adoption and repeat purchases.

The degree to which consumers can draw upon the latter source may, however, be limited for each attribute to recognize that not all of a product's characteristics can be easily evaluated through first-hand experience. As an example from our application case presented in Chapter 6, consider that a consumer is unlikely to be able to precisely assess a fuel's combustion properties or environmental impact just by driving his/her car. In order to incorporate these limitations, we introduce an attribute-specific parameter o_j that determines the observability of attribute j and controls the relative influence of personal experience from post-purchase product evaluation on the formation of product attribute estimates.

4.3.2. Point of sale agents

Let S be a set of points of sale indexed by l. Products are not necessarily available at all points of sale $S_l \in S$ all the time during the simulation. To account for limited availability, let $s_{i,l,t}$ be a binary variable that indicates whether a product is available at point of sale S_l at time t, i.e.

$$s_{i,l,t} = \begin{cases} 1 & \text{iff product } P_i \text{ is available at point of sale } l \text{ at time } t \\ 0 & \text{otherwise.} \end{cases} \tag{4.2}$$

Accounting for availability allows analysts to incorporate supply limitations and assess the effectiveness of varying rollout and distribution strategies.

Product prices may vary at each point of sale over the simulated time span. Accounting for heterogeneity in prices across time and points of sale allows analysts to assess the effectiveness of various pricing strategies, such as price skimming (i.e., starting with a high price and lowering it over time to capture as much of the consumer surplus as possible) or penetration pricing (i.e., starting with a low price to promote fast adoption and raising the price as market penetration increases). To represent pricing in the model, denote by $p_{i,l,t}$ the price of product P_i at point of sale S_l at time t. Pricing policies are defined exogenously by the decision-maker. The model could also easily be extended to allow for adaptive pricing strategies. Points of sale agents could, for example, set their own prices based on local competitors' behavior or exogenous changes (e.g., changes in input prices).

The attraction parameter k_l is consumers' point of sale selection process and can be used to calibrate the model to account for aspects such as a favorable location of the point of sale at a major road, amenities etc..

4.3.3. Consumer agents

We denote by C the set of $n^{consumers}$ heterogeneous consumer agents indexed by k. Each consumer agent $C_k \in C$ is characterized by a number of parameters.

Timing of needs In order to simulate the diffusion of repeatedly purchased products, it is necessary to specify the timing of needs. We assume that agents select a point of sale and purchase one of the available alternatives as soon as a need arises.

To account for heterogeneity in consumers' consumptive behavior, an agent-specific incidence distribution that determines the timing of need events is specified. Formally, denote by I_k a random variable with a distribution function $G_k(t)$ that represents the interpurchase time of consumer k. A major advantage of the continuous time modeling approach is that it is not necessary to impose a discrete temporal structure when scheduling events. Hence, arbitrary distributions can be used to model interpurchase times. In particular, all discrete and continuous distributions implemented in the CERN Colt library (Hoschek, 2004), including the commonly used negative binomial, Erlang-2, Weibull, and exponential distributions, are available in our model implementation.

When selecting a particular type of distribution to use in specific applications, analysts can draw upon the rich literature on stochastic models of interpurchase time. Table 4.2 presents a summary of selected contributions and empirical results. For an overview of interpurchase time models, we refer to the respective section in Wagner and Taudes (1987), the discussion in Gupta (1991), and to Jain and Vilcassim (1991).

Reference	Distributions	Empricial data	Remarks
Ehrenberg (1959)	mixed Poisson (purchase rates Gamma distributed over the population)	various food and toiletry products	good fit to aggregate purchase frequency data
Herniter (1971)	Erlang	facial tissues, aluminium foil, laundry detergent	suggest that Erlang distributions describe households' inter-purchase times better than exponential distributions
Chatfield and Goodhardt (1973)	Erlang-2	detergents, washing-up liquids, razor blades, dentrifice, toilet soap	purchases tend to be somewhat more regular than is suggested by the Poisson assumption
Banerjee and Bhattacharyya (1976)	two-parameter inverse Gaussian, population heterogeneity modeled by the natural conjugate family which has truncated t and modified gamma marginals	toothpaste	good fit
Zufryden (1978)	Erlang-2 (with heterogeneous parameters)	dentrifice	compound brand choice and purchase timing model, good fit to empirical data
Jeuland et al. (1980)	Erlang-2 (with heterogeneous parameters)	cooking oil	compound brand choice and purchase timing model
Lawrence (1980)	left-truncated lognormal	dentrifice	good aggregate fit to purchase frequency data that includes various subgroups of households
Dunn et al. (1983)	Poisson	baked beans, toilet tissue	purchasing at individual stores; Poisson assumption holds for the majority of consumers, but a more "regular" distribution better fits inter-purchase times of heavy buyers

Reference	Distributions	Empricial data	Remarks
Wagner and Taudes (1986)	mixed Poisson (purchase rates Gamma distributed over the population)	detergent	compound brand choice and purchase timing
Gupta (1988)	Erlang-2; scale-parameter treated as a function of marketing variables	coffee	compound brand choice and purchase timing
Jain and Vilcassim (1991)	exponential, Erlang-2, Weibull	coffee	inter-purchase times cannot be adequatly described by probability distributions such as exponential, Erlang-2 or Weibull
Meade and Islam (2010)	Weibull	branded sauce	Copula-based approach; after product introduction, a consumer waits to make the initial purchase and either waits to repurchase or decides not to.

Table 4.2.: Selected empirical studies on inter-purchase time

Depending on consumers' consumptive behavior, $G_k(t)$ may be stationary (continuous consumption), cyclostationary (seasonal patterns), or non-stationary (increasing or decreasing consumption intervals). For many types of frequently purchased products, the timing of consumptive behavior may be adequately approximated with exponentially distributed interpurchase times (cf. Table 4.2) using a Poisson process, i.e., $I_k \sim Pois(\lambda)$. The purchase rate λ may vary across the population to incorporate heterogeneous consumption patterns; to this end, a Gamma distribution is frequently used in mixed Poisson models.

In the biofuel application presented in Chapter 6, we generally use empirically parameterized Poisson streams (based on respondents' reported driving behavior) as the interpurchase time distribution for each consumer agent. For this specific application example, the assumption that the timing of need events can be captured by a stochastic process and that these needs are satisfied immediately is reasonable for most drivers. Needs for fuel arise as consumers' vehicles run low on it and are satisfied by choosing a gas station and refueling.

For different applications, it may be necessary to define mechanisms that determine whether or not agents decide to satisfy a latent need. In particular, for innovations for which there are no established consumption patterns, exogenous generation of need events may also not be appropriate and alternative mechanisms that trigger needs (e.g., advertising) would need to be developed. Although this is beyond the scope of the current thesis, the model could easily be adapted to endogenize the generation of need events and incorporate alternative mechanisms that determine consumptive behavior.

Product awareness Because the model simulates the diffusion of innovations and does not assume perfect information, consumer agents are not necessarily aware of all products available at the market. The spread of information about an innovation through promotional activities and communication is an important model aspect. Consumer agents only consider new products in their purchase decisions once they have become aware of them. To this end, let $a_{i,k}$ be a binary variable that indicates consumer C_k's awareness of product P_i at time t, i.e.,

$$a_{i,k}^{prod} = \begin{cases} 1 & \text{iff consumer agent } k \text{ is aware of product } i \\ 0 & \text{otherwise.} \end{cases} \tag{4.3}$$

We assume that consumers do not forget products over time, i.e. if an agent becomes aware of product P_i at time q, then $a_{i,k}^{prod} = 1$ for $t \geq q$.

For markets where consumers' attention span is particularly short, alternative assumptions about forgetting could be incorporated into the model easily.

Attribute awareness Not only are consumers not necessarily aware of all products available at a market, but they may also not be aware of all criteria that may potentially be relevant for their purchase decisions.

Formally, let $a_{j,k}$ be a binary variable that indicates consumer agents' attribute awareness, i.e.,

$$a_{j,k}^{attr} = \begin{cases} 1 & \text{iff consumer agent } k \text{ is aware of attribute } j \\ 0 & \text{otherwise.} \end{cases} \tag{4.4}$$

This variable affects consumer agents' communication and purchasing behavior. When exchanging product attribute estimates, consumer agents choose topics to discuss from the attributes that they are aware of (cf. Subsection 4.4.2). At the time of purchase, consumer agents also consider only those product attributes that they are aware of (cf. Subsection 4.4.3).

In markets typified by low involvement, consumers are less likely to consider a wide range of attributes than in a market characterized by high consumer involvement (Jager, 2007). When modeling the spread of low involvement products, it is therefore particularly important to account for consumers' scant attention to product attributes and the innovator's challenging task to convince consumers to consider additional attributes.

Attribute awareness is also a particularly important aspect in the diffusion of "game-changing" or "disruptive" innovations. The latter term was coined by Christensen (1997) to describe innovations that are not able to match the performance of existing products in established performance attributes, but rather emphasize new performance attributes in order to differentiate their product from incumbents' offerings and make it attractive to a new customer segment. Disruptive innovations allow innovators to gain entry into a market as a small and low-margin business and to move "up market" later by improving the product to offer good enough performance in old attributes and superior performance in new attributes (Charitou and Markides, 2003).

By accounting for consumer agents' awareness of product attributes, the proposed model incorporates concepts such as the innovator's burden of educating the market about the relevance of new performance dimensions. In the biofuel application presented in Chapter 6, for example, attributes such as range or environmental impact only become relevant once there are products that differ from conventional fuels in these respects.

Preferences To enable researchers and analysts to study the impact of heterogeneous preferences, we define partial utility functions $u_{j,k}(v)$ for each consumer agent C_k and attribute A_j. No specific assumptions regarding the functional form of $u_{j,k}(v)$ are necessary and various forms, including monotonous and ideal point preference models, may be specified. Agent k's partial utility $u_{i,j,k}$ for attribute A_j of product P_i is given as a function of the agent's current attribute value estimation $v_{i,j,k}^{estimate}$, i.e.

$$u_{i,j,k} = u_{j,k}(v_{i,j,k}^{estimate}), \tag{4.5}$$

where $v_{i,j,k}^{estimate}$ is consumer k's estimate of product i's attribute value j. It is calculated based on the limited local information a consumer agent possesses about the product attribute as discussed in Subsection 4.4.1. Summing over all attributes the agent is aware of and adding a random error ϵ yields agent C_k's total utility valuation $u_{i,k}$ of product P_i:

$$u_{i,k} = \sum_{j=1,\dots,n} u_{i,j,k}(v_{i,j,k}^{estimate}) a_{j,k}^{attr} + \epsilon \tag{4.6}$$

The random error $\epsilon \sim (-\epsilon_{range}, +\epsilon_{range})$ is added to capture unexplained variability and randomness. Without loss of generality, we scale $\sum_{j=1,\dots,n} \max\left(u_{j,k}(v_{i,j,k})\right) = 1$.

Price is modeled in the same way as other product attributes; by convention, we denote the price attribute by A_1 and assume that agents are always aware of the price attribute (i.e., $a_{1,k}^{attr} = 1 \quad \forall C_k \in C$). The utility functions $u_{1,k}(v)$ will usually be assumed to be monotonously decreasing.

In our application example, we use piecewise linear partial utility functions and interpolate between part worths measured at various attribute levels in a conjoint experiment. Details on how the subjective information base of each agent is formed through communication and personal experience, as well as impacted by promotional activities, are discussed in Sections 4.4.2, 4.4.4, and 4.4.5, respectively.

Miscellaneous agent characteristics For the application case presented in Chapter 6, additional parameters that characterize consumers' mobility behavior are also taken into account. The model extensions for the biofuel example application are outlined in Subsection 6.2.2.

4.3.4. Space

The model accounts for spatially disaggregated social interaction effects. We position consumer agents and points of sale in a continuous two-dimensional space. The locations of these agents are relevant for point of sale selection processes (cf. Subsection 4.4.3) and determine the link probabilities between agents in the spatially explicit algorithm for constructing synthetic social networks, which we will outline in Subsubsection 4.3.5.4. We use a geographical coordinate system and denote by $L_k^{cons} = (\rho_k, \lambda_k)$ the location of consumer agent k and by $L_l^{pos} = (\rho_l, \lambda_l)$ the location of point of sale l. Latitudes ρ and longitudes λ are expressed in degrees.

Note that the standard generative algorithms (random, small-world, scale-free) for constructing (social) network graphs introduced in Sections 4.3.5.1 – 4.3.5.3 are not defined in geographic space. In non-spatial simulation scenarios, we therefore arbitrarily assign $L_k^{cons} = (0, 0)\ \forall\ C_k \in C$ and $L_l^{pos} = (0, 0)\ \forall\ S_l \in S$.

Locations of all consumer agents and points of sale are assigned during initialization of the model and remain fixed during simulation runs. In our real-world application presented in Chapter 6, consumer agents are distributed in geographic space according to the region's measured population density and points of sale are placed at their actual geographical location.

4.3.5. Social network

Consumer agents are embedded in a social network that structures interactions between individual members of the social system. The network of social contacts is represented by a weighted and directed graph $G = (C, E)$. C is the set of consumer agents (i.e., the set of vertices in the graph), and E is the set of communication links (i.e., edges) between them. This graph can be represented in a $|C| \times |C|$ weighted adjacency matrix given by

$$W_{a,b} = \begin{cases} w_{a,b} \in (0, 1] & \text{iff } \{C_a, C_b\} \in E \\ w_{a,b} = 0 & \text{otherwise.} \end{cases} \tag{4.7}$$

The weights $w_{a,b}$ represent the impact of the information agent C_b receives from consumer agent C_a and therefore the influence of C_a on the attribute value estimates of C_b (cf. Subsection 4.4.2). An example graph and the corresponding weighted adjacency matrix are provided in Figures 4.3 and 4.4, respectively.

Since it is assumed that consumer agents do not exchange information with themselves, there will usually be no loops present in G and hence all entries of the main diagonal of A are zero (i.e.,

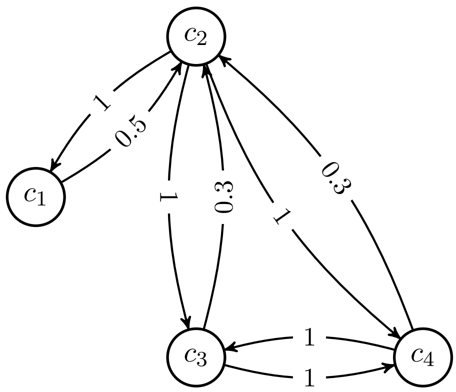


Figure 4.3.: Example social network graph

$$W = \begin{array}{c} \\ c_1 \\ c_2 \\ c_3 \\ c_4 \end{array} \begin{array}{c} \begin{array}{cccc} c_1 & c_2 & c_3 & c_4 \end{array} \\ \begin{pmatrix} 0 & 0.5 & 0 & 0 \\ 1 & 0 & 1 & 1 \\ 0 & 0.3 & 0 & 1 \\ 0 & 0.3 & 1 & 0 \end{pmatrix} \end{array}$$

Figure 4.4.: Example adjacency matrix

$A_{a,b} = 0 \quad \forall a = b$). Alternatively, self loops could be introduced to incorporate the idea of self-reinforcement of estimates over time. This would reflect the notion that it becomes increasingly hard to convince individuals to change their opinions once they have formed a firm conviction.

Different markets imply different network structures of consumers (Delre et al., 2010). A number of generative algorithms developed in the graph modeling literature exhibit characteristics of real-world social networks and have therefore been used as stylized synthetic social networks in agent-based models of innovation diffusion. For an overview, cf. Subsection 3.3.3. To account for different network structures in different markets, our model and the simulation tool that implements it incorporate a number of established algorithms that have been put forth in the literature. In addition, we introduce a graph model that explicitly accounts for spatial proximity when constructing the (social) network, which is based on prior work by Manna and Sen (2002) as well as Yook et al. (2002). In the remainder of this section, we briefly outline each of the generative algorithms implemented in the model.

4.3.5.1. Gilbert (1959)

Random graphs are frequently used to structure interactions in agent-based innovation diffusion models (cf. the literature review in Chapter 3), even though they lack characteristic features of real-world social networks. This notwithstanding, they may appropriately represent certain markets with a highly random interaction structure and serve as a "baseline" for comparison with other topologies.

A random network model based on two parameters, the number of vertices n and the edge probability p^{link} was proposed and analyzed by Gilbert (1959) in a telecommunications context. It is very similar to the Erdős and Rényi (1960) graph model, which uses the number of edges instead of the link probability as a second parameter, and is frequently attributed to the latter authors in the literature. Both algorithms generate graphs in which edges are independent and each edge is equally likely.

The model proposed by Gilbert (1959) constructs graphs by linking each of the $\frac{n(n-1)}{2}$ pairs of vertices independently with probability p^{link} (cf. Algorithm 2). This is equivalent to picking randomly from the $2^{\frac{n(n-1)}{2}}$ possible graphs, using p^{link} as a weighting function.

Algorithm 2 Gilbert (1959) random network model

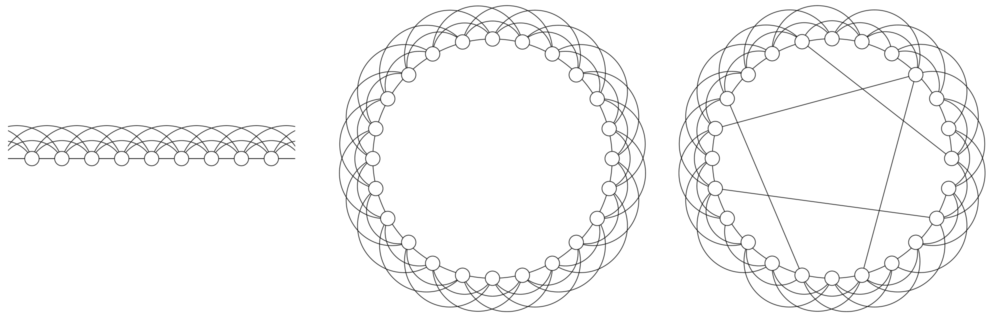
1. Start with n unlinked vertices
2. For each pair of vertices, add an edge with independent probability p^{link}

4.3.5.2. Watts and Strogatz (1998)

Networks that have a small diameter and are also highly clustered are called small-world networks. To generate small-world networks in our model, we use the generative algorithm developed by Watts and Strogatz (1998), which interpolates between random and regular networks. In a regular lattice, each node is connected to its z nearest neighbors, as illustrated in Figure 4.5a. Figure 4.5b shows the same lattice when periodic boundary conditions are applied so that the graph wraps around on itself in a ring. In regular lattices, immediate neighbors of any node are also connected to one another, which yields a highly clustered network. More precisely, the value of the clustering coefficient (cf. Subsection 3.3.2) in a regular lattice with periodic boundary conditions in general dimension d is

$$C^{lattice} = \frac{3(z-2d)}{4(z-d)}, \tag{4.8}$$

which tends to $\frac{3}{4}$ for $z \gg 2d$ (Newman, 2000). However, as can be intuitively seen from Figure 4.5a and 4.5b, diameter and characteristic path lengths of low-dimensional regular lattices are large. More precisely, for a regular lattice in d dimensions, the average node-to-node distance increases as $N^{1/d}$ (Newman, 2000). As Watts and Strogatz (1998) show, introducing some degree of randomness into the network rapidly decreases the characteristic path length while the network still remains highly clustered. They suggest a specific scheme for doing this (cf. Algorithm 3) which starts with a ring lattices and randomly "rewires" a fraction of the edges.



(a) (b) (c)

Figure 4.5.: (a) A one-dimensional lattice with each site connected to its $z = 6$ nearest neighbors; (b) The same lattice with periodic boundary conditions; (c) The Watts-Strogatz model is created by rewiring a small fraction of the links (in this case 5 of them) to new sites chosen at random.
Source: Newman (2000)

Algorithm 3 Watts and Strogatz (1998) small-world network model

1. Arrange n vertices in a ring lattice of and connect each vertex to its k^{watts} nearest neighbors
2. Iterate over all edges and with probability β^{watts}, move one end to a randomly chosen new position

For small β^{watts}, this produces a graph which is still mostly regular but has a few "shortcuts" which stretch a long distance across the lattice (cf. Figure 4.5c). These shortcuts greatly reduce the diameter and characteristic path length of the graph. In social terms, this corresponds to the idea that social ties tend to form clusters in an abstract social space (e.g., neighbors in the same street, people who work at the same institution, people who share similar interests etc.) and that some people are also friends with some other people who are a long way away, in some social sense (Newman, 2000).

4.3.5.3. Barabási and Albert (1999)

Many social networks exhibit the scale-freeness property, i.e., the probability $P(k)$ that a node in the network is connected to k other nodes decays as a power law, following $P(k) \sim k^{-\lambda}$ (Barabási and Albert, 1999). A network model that captures this characteristic was proposed by Barabási et al. (1999). The algorithm differs fundamentally from those introduced above in that it forms the network by continuous addition of new vertices to the system rather than starting with a fixed set of n vertices that are randomly connected (Erdős and Rényi, 1960) or reconnected (Watts and Strogatz, 1998). Barabási et al. motivate this approach by the idea that many real-world networks are open and grow over time. The proposed algorithm (cf.

Algorithm 4) is defined in two steps: an initialization step with a fixed number of fully connected initial vertices, and an iterative growth procedure with preferential attachment.

Algorithm 4 Barabási and Albert (1999) scale-free network model

1. Start with $n_{init}^{barabasi}$ fully connected "seed" vertices
2. Iteratively add vertices one by one and connect each to $n_{connect}^{barabasi}$ (where $n_{connect}^{barabasi} \leq n_{init}^{barabasi}$) existing vertices. The probability Π that a new vertex will be connected to vertex k depends on the connectivity c_k of that vertex, such that

$$\Pi(C_k) = \frac{c_k}{\sum_l c_l}$$

After x steps the algorithm yields a random network with $n = x + n_{BA}^{init}$ vertices and $n_{BA}^{connect}x$ edges. The network self-organizes into a scale-invariant state, the probability that a vertex has k edges following a power law with an exponent $\lambda_{BA} = 2.9 \pm 0.1$ (Barabási et al., 1999), which approximates empirically observed degree distributions (Barabási and Bonabeau, 2003, also cf. Subsection 3.3.2).

The mechanism used to attach existing nodes with probabilities according to the degree of the target node incorporates the idea of preferential attachment. This term was coined by Barabási et al. (1999) in a complex networks context to refer to ideas that already existed in different contexts in the literature (Price, 1976, for example, refers to the concept as a "cumulative advantage processes"). The more connected a node is, the more likely it is to attract new links. The resulting network contains a few important nodes, or hubs, with a seemingly unlimited number of links. Furthermore, no node in the network is typical of the others (Barabási and Bonabeau, 2003).

Due to their highly skewed degree distribution, the resulting networks are suitable for studying roles of opinion leaders (hubs), but they are typically not highly clustered. The small-world and scale-free network models may be viewed as rival models, but they can alternatively be considered models that focus on different aspects of networks. For different market types and conditions, these aspects (role of high clustering vs. role of hubs) may be of varying importance and together, they should cover most of the parameters relevant to the marketing context (Goldenberg et al., 2007).

4.3.5.4. Spatial graph model (Manna and Sen, 2002; Yook et al., 2002)

None of the network models discussed so far is defined in geographical space. To create a spatially explicit model, we need to account for the tendency of people in the same locality to form bonds and therefore to be more likely to know and influence each other (cf. Latane et al., 1995). To this end, the spatial distance between nodes needs to be considered when constructing links. More precisely, the intensity of the communication process is assumed to decay with the spatial distance between individuals. In prior research, it was assumed that this decay usually follows a Newtonian-type inverse power law or a negative exponential function (Morrill et al., 1988, Chapter 5, as cited in Emmanouilides and Davies, 2007). Hence, we use an Euclidean network model in which the attachment probability of the Barabási et al. (1999) model is modulated by a factor related to the distance $\ell(i, j)$ between the two nodes. A similar model was proposed by Manna and Sen (2002) and applied by Yook et al. (2002) for modeling the Internet's large-scale topology. Our implementation of this network model differs slightly from the original formulation in that we link each incoming node not necessarily to a single, but more generally to $n_{link}^{spatial}$ existing nodes. The influence of clustering and geographic distance are controlled by the exponents $\alpha^{spatial}$ and $\beta^{spatial}$, respectively. The procedure that constructs the network is specified in Algorithm 5.

Algorithm 5 Spatial network model (cf. Manna and Sen, 2002; Yook et al., 2002)

1. Start with $m_{init}^{spatial}$ fully connected "seed" vertices
2. Iteratively add vertices one by one and connect each incoming vertex j to $n_{link}^{spatial}$ existing vertices. In particular, connect to vertex i of degree c_i with a link of length $\ell(i, j)$ using a probability proportional to $c_i^{\beta} \ell^{\alpha}$ (considering only those target vertices which are not yet linked to the current vertex).

Note that for $\alpha^{spatial} = 0$ and $\beta^{spatial} = 1$, the network model corresponds to the Barabási et al. (1999) model. In order to favor local links, we will typically choose a negative value for the geodesic exponent $\alpha^{spatial}$. For a limited range of parameters $\alpha^{spatial}$ and $\beta^{spatial}$, the model exhibits all three main characteristic features of social networks, i.e., small diameter, high clustering, and scale-freeness (Sen and Manna, 2003). Figure 4.6 illustrates a number of sample networks for varying values of $\alpha^{spatial}$ and $\beta^{spatial}$ with $|V| = 100$ vertices that are randomly distributed in space, and $|E| = 200$ edges.

4.4. Model mechanisms

Having defined all model entities in the previous section, this section adopts a dynamic perspective and discusses the mechanisms that shape the behavior of the model.

4.4.1. Information flows

A key mechanism in the proposed model is the spread of information about products and their characteristics through multiple channels in the social system. As consumer agents learn more

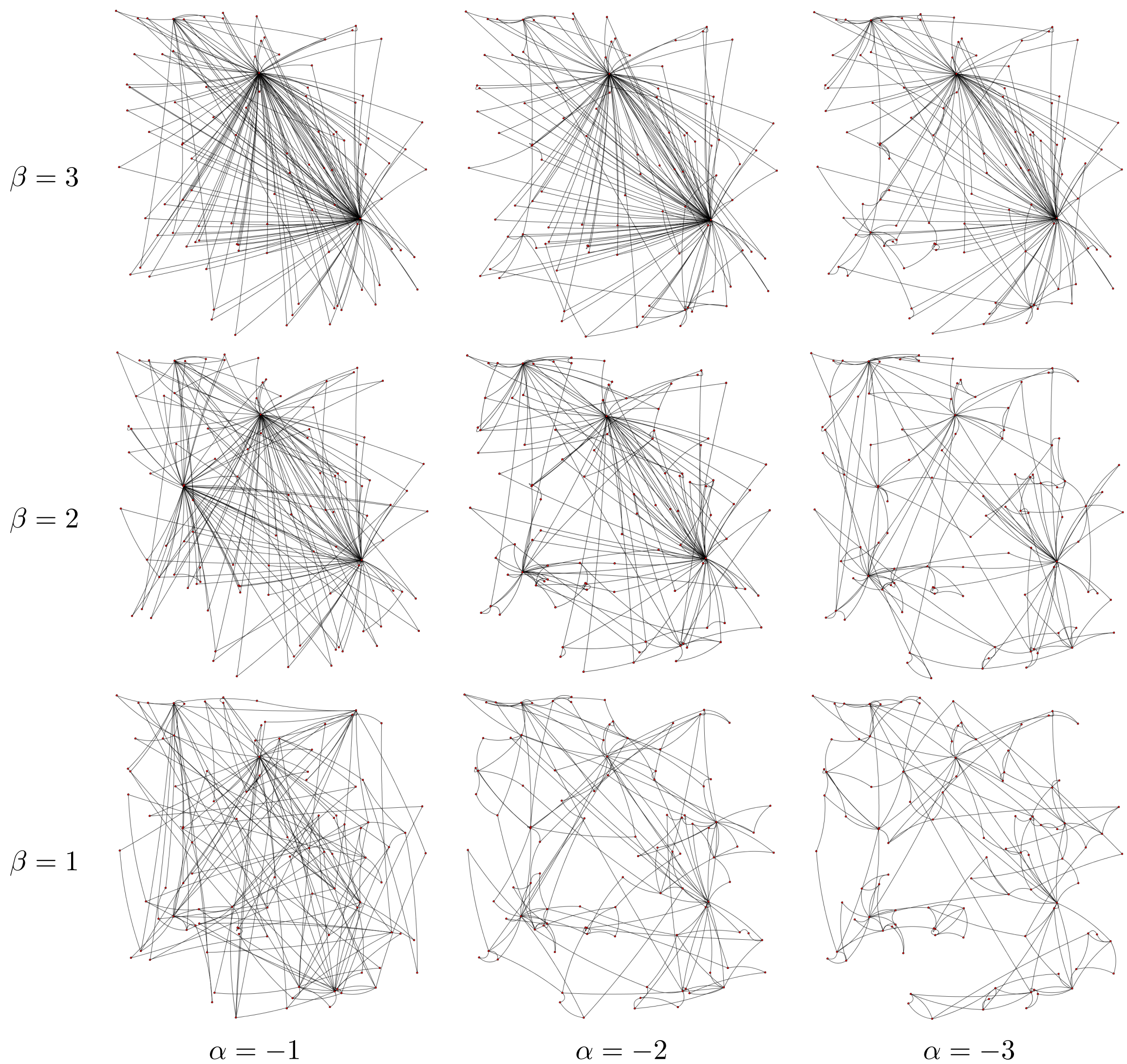


Figure 4.6.: Sample spatial networks for varying values of $\alpha^{spatial}$ and $\beta^{spatial}$ with randomly distributed vertices

about the innovation from external sources (e.g., advertising, word of mouth) and from personal experience in using the product, their uncertain perceptions about the innovation adapt over time. This learning mechanism also affects utility expectations and may lead to adoption once the agent expects sufficient advantages over alternative products. To keep track of information about products' characteristics, consumer agents store attribute value information in histograms. In particular, each consumer agent C_k keeps a histogram for each attribute A_j of each product P_i. Note that attribute value estimates, rather than utility estimates, are stored.

Product attribute information is classified into n^{bins} histogram bins. Denote by $h_{i,j,k,g=1}, \dots,$ $h_{i,j,k,n^{bins}}$ the value of histogram bin g (i.e., the "height" of the respective histogram bar). The range of the histogram for attribute A_j is defined in the interval (v_j^{min}, v_j^{max}). Hence, the range of values (v_j^{min}, v_j^{max}) is divided into n^{bins} equally spaced categories, where n^{bins} controls the "resolution" of attribute value estimates. The "width" of one histogram bin for attribute A_j is therefore given by $\frac{v_j^{max} - v_j^{min}}{n^{bins}}$.

Updating procedure The updating procedure that adjusts the histogram upon arrival of new information is as follows. The new information is weighted with a factor w, which depends on the source of the information. In case the information is obtained from other consumers via WoM, the influence weight $w_{a,b}$ of the respective edge in the social network is used; if the attribute value is communicated via advertising messages, an advertising impact factor w^{ad} is used; finally, the observability o_j of the attribute is used to weight attribute value estimates from first-hand experience in post purchase evaluations. The relative magnitude of these weights for different information channels determines the relative impact of WoM, advertising, and first-hand experience, respectively. The bin g into which the value v falls is updated as specified in Algorithm 6.

Algorithm 6 Attribute information inflow

$$h_{i,j,k,g} \leftarrow h_{i,j,k,g} + we^{t\lambda}$$
$$\text{where } w = \begin{cases} w_{a,b} & \text{for communication events} \\ w^{ad} & \text{for advertising events} \\ o_j & \text{for post purchase evaluation events.} \end{cases}$$

The weight w is multiplied by $e^{t\lambda}$, where t is the current simulation time, to introduce exponential decay at rate $\lambda \geq 0$ by weighting new information with higher weights and thereby reducing the relative importance of old information.

Attribute value estimates Agent k's current attribute value estimate $v_{i,j,k}^{estimate}$ for attribute A_j of product P_i is obtained by averaging over the distribution in the histogram. In particular, the value $v_{i,j,k}^{estimate}$ is obtained by multiplying the "height" of each bar $h_{i,j,k,g}$ by the medium value of the respective bin, summing up over all bins, and dividing the result by the total height of all bars, i.e.,

$$v_{i,j,k}^{estimate} = \frac{\sum_{g=1}^{n^{bins}} \left(h_{i,j,k,g} \left(v_j^{min} + (g - \frac{1}{2}) \frac{v_j^{max} - v_j^{min}}{n^{bins}} \right) \right)}{\sum_{g=1}^{n^{bins}} h_{i,j,k,g}}. \tag{4.9}$$

The histogram approach avoids immediate lossy aggregation of information (e.g., storing only a single average value) by keeping track of the distribution of information received for each attribute. Although for the mechanisms currently implemented in model, it would be sufficient to store average values, the histogram approach is more extensible in that it allows for model modifications that take the distribution of the information received into account.

4.4.2. Communication events

It is well documented that WoM, which is not directly under the decision maker's control, plays a powerful role in the diffusion of innovations (Mahajan et al., 1990). To incorporate this important aspect, we define a mechanism that captures consumers' WoM referral behavior.

Scheduling A stochastic process $Y_{a,b}$ is attached to each link connecting consumer agents C_a and C_b in the social network to determine the timing of communication events. An arbitrary distribution implemented in the CERN Colt library (Hoschek, 2004) can be used as an interarrival time distribution from which the time until the next communication event is drawn. In our simulation experiments, we applied a Poisson stream to reflect our assumption of exponentially distributed interarrival times. Figure 4.7 illustrates the scheduling of communication events. The first communication event on each edge is scheduled during the initialization procedure. The time of the first occurrence is drawn from $Y_{a,b}$. Each time a communication event is processed, a new communication event is scheduled at the end of the process, again by drawing from the interarrival time distribution $Y_{a,b}$ and adding the value drawn to the current simulation time t.

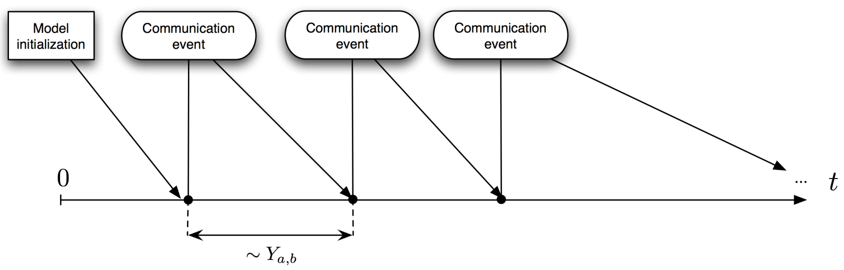


Figure 4.7.: Scheduling of communication events for each social network link

Event execution Each scheduled communication event is executed in three steps:

1. Selection of a list of topics to exchange information on,
2. actual information exchange, and
3. scheduling of the next communication event on the respective network edge.

The first step of the process is performed by each agent individually to determine the set of topics the agent is interested in exchanging information on. The process for selecting communication topics follows Algorithm 7, which is based on the assumption that the probability that consumers pass on information that they have obtained about specific product characteristics depends on the change in utility estimates that this new information has caused. Usually, one can reasonably expect that the larger the change in a consumer's utility estimates with respect to a product attribute, the more important is that change for the respective consumer and therefore the larger the probability that he/she will pass on the information about the respective product attribute in WoM communication. This change in utility depends on the personal preferences of the respective consumer so that consumer agents are more likely to talk about attributes that contribute a large partial utility than about those that are of marginal importance. We formalize the topic selection mechanism by means of a real-valued function $p^{comm}(\Delta u_{i,j,k})$ that assigns a selection probability to a given change in attribute utility valuation. Because the maximum obtainable utility value is scaled to 1, i.e., $\sum_{j=1,\ldots,n} \max\big(u_{j,k}(v_{i,j,k})\big) = 1$, this function has to be defined in the interval $[0, 1]$. In defining this function for our application study in Chapter 6, we made the following specific assumptions:

1. *"Consumers only talk, when they have something to say"*
   As long as a consumer does not obtain any new information that changes his/her perceived utility of a product characteristic, he/she is unlikely to pass on information about it.
2. *"Consumers will pass on information about a product characteristic if it is important and not expected"*
   The larger the change in the estimated partial utility, the higher the probability that a consumer will pass on the information via WoM.
3. *"Bad news travel fast"*
   Consumers are more likely to pass on WoM if they are disappointed, i.e., if there is a negative change in estimated partial utility. In our experiments, we therefore defined $p^{comm}(\Delta u_{i,j,k})$ as a asymmetric U-shaped function that has its minimum at zero.

The latter assumption is supported by marketing research on WoM communication, which suggests that dissatisfied consumers engage in more WoM than satisfied customers (cf. Arndt, 1967; Richins, 1983, 1987; Hart et al., 1990; Charlett et al., 1995; Anderson, 1998). In a service context, for example, Hart et al. (1990) find that consumers with memories of poor service tell approximately eleven people while those with pleasant recollections tell only six. Anderson (1998), also find that the hypothesized asymmetric U-shaped functional form of the relationship between satisfaction and WoM cannot be rejected using data from the United States and Sweden. More recent research (East et al., 2007) has questioned the hypothesis that negative WoM generally occurs more often in absolute terms, and that negative WoM has a stronger impact than positive WoM (East et al., 2008). For the specific application case study in Chapter 6, however, based on the wealth of literature, it appears reasonable to assume that the *conditional probability* that consumers engage in WoM is higher in the case of negative experiences. The model can also easily be adapted to reflect alternative assumptions by changing the shape of $p^{comm}(u_{i,j,k})$.

Algorithm 7 returns a set of topics T which is the union of the topic sets selected individually by the communicating agents C_a and C_b. For each of these agents, the algorithm iterates over all attributes of all products to determine whether to consider each of them based on the probability that $p^{comm}(u_{i,j,k})$ assigns to the change in partial utility estimate since the last time the agents communicated, denoted by $\Delta^{(a,b)}u_{i,j,k}$ and $\Delta^{(b,a)}u_{i,j,k}$ for agents C_a and C_b, respectively. To this end, let $X(\omega)$ be a real-valued, continuous random variable equidistributed on $[0, 1]$. If the realization $x = X(\overline{\omega})$ drawn is smaller than the probability $p^{comm}(u_{i,j,k})$, then the algorithm selects the respective product attribute by adding the topic (P_i, A_j) to T. The same procedure is repeated for agent C_b (lines 8–13) and the union of the topics chosen by each agent individually is returned.

Algorithm 7 Communication topic selection

1: **for all** $P_i \in P$ for which $a^{prod}_{i,a} = 1$ **do**
2:     **for all** $A_j \in A$ for which $a^{attr}_{j,a} = 1$ **do**
3:         **if** $x = X(\overline{\omega}) < p^{comm}\left(\Delta^{(a,b)}u_{i,j,k}\right)$ **then**
4:             $T \leftarrow T \cup (P_i, A_j)$
5:         **end if**
6:     **end for**
7: **end for**
8: **for all** $P_i \in P$ for which $a^{prod}_{i,b} = 1$ **do**
9:     **for all** $A_j \in A$ for which $a^{attr}_{j,b} = 1$ **do**
10:         **if** $x = X(\overline{\omega}) < p^{comm}\left(\Delta^{(b,a)}u_{i,j,k}\right)$ **then**
11:             $T \leftarrow T \cup (P_i, A_j)$
12:         **end if**
13:     **end for**
14: **end for**
15: **return** T^{list}

Once the set of potential topics T^{list} has been determined, the actual information exchange is performed according to Algorithm 8. The algorithm iterates over all topics (i.e., product-attribute pairs) in the set of topics T. If both communicating consumer agents are aware of the current attribute as well as the current product, then information flows in both directions. The current attribute value estimates $v_{i,j,a}^{estimate}$ and $v_{i,j,b}^{estimate}$ are calculated by averaging over the information in the respective histogram $h_{i,j,k}$ (cf. Equation 4.9). The values $v_{i,j,a}^{estimate}$ and $v_{i,j,b}^{estimate}$ passed as an argument to *informationInflow*(), which is specified in Algorithm 6, represent the attribute value estimates before updates by the current communication event are made to the histogram. The subscripts a and b indicate the target consumer agent of the information flow. In the object-oriented implementation of the model outlined in Chapter 5, this function is implemented as an instance methods of the `ConsumerAgentBase` class.

In case one of the agents was unaware of an attribute and/or a product before the communication event, information flows unidirectionally from the aware to the unaware agent. Lines 11,15, 19, and 20 ensure that agents' awareness variables $a_{j,a}^{attr}$ and $a_{i,a}^{prod}$ are updated to reflect that the agent has become aware of attribute A_j or product P_i, respectively.

Algorithm 8 Communication event processing

Require: set of topics $T = \{(P_i,\, A_j), \dots\}$

1: **for all** $(P_i,\, A_j) \in T$ **do**
2:   **if** $a_{j,a}^{attr} = 1$ and $a_{j,b}^{attr} = 1$ **then**
3:     **if** $a_{i,a}^{prod} = 1$ **then**
4:       $\mathit{informationInflow}_a(P_i, A_j, v_{i,j,a}^{estimate}, w_{a,b})$
5:     **end if**
6:     **if** $a_{i,b}^{prod} = 1$ **then**
7:       $\mathit{informationInflow}_b(P_i, A_j, v_{i,j,b}^{estimate}, w_{b,a})$
8:     **end if**
9:   **else**
10:     **if** $a_{j,a}^{attr} \neq 1$ **then**
11:       $a_{j,a}^{attr} \leftarrow 1$
12:       $\mathit{informationInflow}_a(P_i, A_j, v_{i,j,b}^{estimate}, w_{b,a})$
13:     **end if**
14:     **if** $a_{j,b}^{attr} \neq 1$ **then**
15:       $a_{j,b}^{attr} \leftarrow 1$
16:       $\mathit{informationInflow}_b(P_i, A_j, v_{i,j,a}^{estimate}, w_{a,b})$
17:     **end if**
18:   **end if**
19:   $a_{i,a}^{prod} \leftarrow 1$
20:   $a_{i,b}^{prod} \leftarrow 1$
21: **end for**

4.4.3. Need events

As noted above, we assume that needs are satisfied immediately and therefore treat need and purchase as a single event.

Scheduling Since the diffusion model is designed for simulating the spread of non-durable or frequently purchased products that are consumed on a regular basis, these events are generated repeatedly by a stochastic process that follows an interpurchase distribution $G_k(t)$ that can be parameterized individually for each consumer agent. No specific assumptions about the family of distributions $G_k(t)$ belongs to have to be made.

The purchasing process triggered by a need event can be divided into the following stages:

1. point of sale selection,
2. evoked set construction,
3. price information inflow,
4. utility estimation, and
5. final purchase decision.

Point of sale selection For many non-durable or frequently purchased consumer items, it is reasonable to assume that consumers first choose the point of sale and then decide which of the available products to purchase at the point of sale, rather than first selecting a product and then choosing a point of sale that carries it. Several alternative approaches for choosing a point of sale are conceivable, e.g., (i) each consumer may use the same point of sale for every purchase made, (ii) consumers may pick a different point of sale for each purchase made, or (iii) consumers may use a combination of the two approaches. In the latter case, they may use one of several preferred points of sale most of the time, but also choose other points of sale randomly from time to time. The proposed model incorporates an algorithm that can implement all of these alternative assumptions about how consumers decide where to purchase.

The procedure is outlined in Algorithm 9 and incorporates two alternative mechanisms for selecting a point of sale: (i) with probability $p_k^{recentPOS}$, choose from the $n_k^{posHist}$ most recently visited points of sale; in particular, select the point of sale where the previous purchase yielded the highest utility; (ii) with probability $1 - p_k^{recentPOS}$, choose a random point of sale with probabilities inversely proportional to the distance between the consumer agent's residential location and the point of sale, weighted with an exponent $\alpha_k^{posSelect}$ and an attraction factor k_l

The first mechanism is formalized in lines 2–10 of the algorithm. A random error $\epsilon^{pos} \sim U(-\varepsilon^{pos}, +\varepsilon^{pos})$ is added to the utility of the previous purchase at each point of sale to account for unexplained variability and consumers' imperfect memory. Line 12 incorporates the second mechanism. At the end of the process, the queue S_k^{hist} is updated by removing the tail element if the queue is full (lines 15-18) and adding the point of sale S_l chosen to the head of the queue.

Algorithm 9 Point of sale selection procedure

if $|S_k^{hist}| > 0$ and $x = X(\overline{\omega}) \leq p^{recentPOS}$ **then**
  $u_{max} = 0$
  for all $S_l \in S_k^{hist}$ **do**
    $u_l = u_l^{hist} + \epsilon^{pos}$
    if $u_l > u_{max}$ **then**
      $S_{max} = S_l$
      $u_{max} = u_l$
    end if
  end for
  $S_{use} = S_{max}$
else
  choose S_{use} with probabilities proportional to $\Pi(S_l) \sim \frac{1}{\ell(k,l)^{\alpha_k^{posSelect}}} a_k$
end if

if $|S_k^{hist}| > n_k^{posHist}$ **then**
  poll S_k^{hist}
end if
$S^{hist} \xleftarrow{add} S_l$

return S_{use}

The parameters $p_k^{recentPOS}$ (probability of selecting a recently visited point of sale), $n_k^{posHist}$ (point of sale history size), $\alpha_k^{posSelect}$ (geodesic weighting exponent), and ε_k^{pos} (point of sale selection error range) are agent-specific and can be initialized individually based on empirical data. If $p_k^{recentPOS} = 1$, then points of sale are chosen randomly only at the beginning of the simulation and once the queue S_k^{hist} is full, the same points of sales are chosen for the remainder of the simulation. If $p_k^{recentPOS} = 1$, by contrast, points of sale are chosen randomly for each purchase. In the biofuel application, we parameterize agents individually based on respondents' reported gas station choice and mobility behavior.

It is assumed that once a need arises, it is always satisfied by purchasing one of the products available at the chosen point of sale, rather than visiting a different point of sale if the preferred choice is not available. For our biofuel application, this assumption appears reasonable. The remaining stages of the purchasing process are formalized in Algorithm 10.

Evoked set construction The first step of Algorithm 10 consists in constructing the evoked set E of alternatives actually considered in the decision process (cf. Narayana and Markin, 1975). We assume that consumers consider all alternatives they are aware of and that are available at

Algorithm 10 Purchasing process

Require: selected point of sale S_l

1: **for all** $P_i \in P$ for which $a_{i,k}^{prod} = 1$ **do**
2:     **if** $s_{i,l,t} = 1$ **then**
3:         $E \xleftarrow{add} P_i$
4:     **end if**
5: **end for**
6: **for all** $P_i \in E$ **do**
7:     $informationInflow_k(P_i, A_1, p_{i,l,t}, w = 1)$
8:     $u_{i,k} = u_{i,1,k}(p_{i,l,t}) + \sum_{j=2,\ldots,n} u_{i,j,k}(v_{i,j,k}^{estimate}) a_{j,k}^{attr} + \epsilon^{prod}$
9: **end for**
10: choose P_{max} for which $u_{max,k} = max(u_{i,k})$
11: $u_l^{hist} = u_{x,k}$
12: **return** P_{max}

the point of sale. More precisely, the two necessary and sufficient conditions for a product to be considered are: (i) $a_{i,k}^{prod} = 1$, and (ii) $s_{i,l,t} = 1$. If these conditions are satisfied for product P_i, then it is added to the evoked set E (cf. lines 1–5 of Algorithm 10) .

Price information inflow In the next step, the consumer agent obtains price information on the available alternatives (cf. line 7 of Algorithm 10). The true price at the point of sale is assumed to be perfectly observable and price information is therefore weighted with $w = 1$. The price information is processed by the standard information inflow algorithm outlined in Subsection 4.4.1. Because prices are neither necessarily uniform across points of sale, nor across time, price information is treated just like other, more uncertain attributes. Hence, even though prices may be perfectly observable at a specific point in time at a single point of sale, the distribution of the price information collected is stored to capture the formation of expectations about price levels.

Evaluation of the evoked set Next, a utility value is calculated for each product in the evoked set (cf. line 8 of Algorithm 10) based on the agent's current estimate of each product attribute $j = 2, \ldots, n$, the price $p_{i,l,t}$, and the agent's individual preferences embodied in the partial utility functions $u_{i,j,k}()$. Note that the actual price $p_{i,l,t}$ rather than the subjective price estimate $v_{i,1,k}$ is used to calculate the partial utility of the price attribute because consumers are assumed to base their purchase decision on actual current prices at the point of sale. The total utility is calculated by summing up partial utilities over all the attributes an agent is currently aware of, i.e. only those attributes A_j for which $a_{j,k}^{attr} = 1$ are considered. Finally, a random error $\epsilon^{prod} \sim (-\varepsilon^{prod}, +\varepsilon^{prod})$ is added to the utility of each alternative to capture unexplained variability and randomness.

In our application case experiments, we used piecewise linear partial utility functions and obtained preference data by means of a conjoint analysis. The partial utility values from the conjoint analysis were interpolated to form piecewise linear utility functions for each attribute.

Final purchase decision The purchase decision is made by choosing the alternative that maximizes total utility. Finally, the utility history u_l^{hist} that stores the utility obtained at the last purchase made at point of sale S_l is updated and the product P_{max} that maximizes estimated utility is returned.

4.4.4. Post purchase evaluation events

Consumers obtain information about a product not only through WoM and advertising, but also through post purchase evaluation after initial adoption and repeat purchases.

Scheduling First-hand usage experience is triggered by product purchases, which may entail the scheduling of a single or multiple post purchase evaluation events. In our simulation experiments, a single experience event was scheduled each time a purchase occurred. The time for the post purchase evaluation event was drawn randomly in the interval between the time of purchase and the next scheduled need event.

Execution Post purchase evaluation based on personal experience yields new information regarding the estimated attribute values of the purchased product. As noted in Subsection 4.3.1, the degree to which consumers can draw upon first-hand experience depends on the observability o_j of the respective attribute, since some product characteristics can be estimated more easily and directly than others.

Algorithm 11 outlines the post purchase evaluation procedure. The algorithm iterates over all attributes the agent is aware of and, using Algorithm 6 outlined in Subsection 4.4.1, adds the “true” attribute value $v_{i,j,k}^{true}$ weighted with its observability o_j to the respective attribute information histogram.

Algorithm 11 Post purchase evaluation procedure

Require: purchased product P_i

for all $A_j \in A$ for which $a_{j,a}^{attr} = 1$ **do**
  $informationInflow_k(P_i, A_j, v_{i,j,k}^{true}, o_j)$
end for

4.4.5. Advertising events

As a final mechanism, we consider that firms launching an innovation typically engage in communication activities to actively spread information about the new product. Mass media advertising is arguably still the most commonly used communication instrument at a decision-maker's disposal. In the marketing of convenience products, advertising at the point of sale is also an important marketing instrument to raise awareness of the product and persuade consumers to purchase it. In order to model advertising, we introduce advertising events that can represent various kinds of promotional activities.

We model advertising communication and WoM communication mechanisms in a very similar manner, but account for two major differences between them. First, and most obviously, advertising information flows are always unidirectional. Second, their impact is typically smaller than that of WoM communication, as evidence from the marketing literature suggests. Day (1971), for example, found in an empirical study on the introduction of new branded convenience food products that WoM was nine times as effective as advertising at converting unfavorable or neutral predispositions into positive attitudes. It is also hypothesized in the marketing literature that the importance of new product advertising lies more in spreading awareness of the product than in influencing the consumer at the critical stage of evaluating it, in which WoM has a much larger impact (cf. Sheth, 1971). In our model, a weighting factor w_r^{adv} that determines the impact of advertising messages relative to the influence of personal experience (controlled by the observability parameter o_j) and influence in the social network (controlled by influence weights $w_{a,b}$), is used to reflect this assumption. In particular, we will choose a lower value for w_r^{adv} than for the consumer communication influence weights $w_{a,b}$ in our simulation experiments.

In the proposed model, we account for the content of advertising messages by explicitly modeling the communicated product attribute values. Each advertising event is therefore characterized by a set of communicated attribute values $T^{adv} = \{(P_i, A_j, v), \ldots\}$, i.e., a collection of triplets consisting of a product P_i, an attribute A_j, and a communicated attribute value v. Advertising may have two distinct effects. It may (i) make a consumer aware of the product with probability $P_r^{makeAware}$, or (ii) impact consumers that are already aware of the product with probability $P_r^{impactAware}$. We distinguish between two types of advertising, each of which incorporates both of these effects: point of sale advertising and mass advertising.

4.4.5.1. Point of sale advertising activities

Each point of sale advertising activity occurs in a specific time span, defined by parameters t_r^{from} and t_r^{till}, at a set of specific points of sale R_r^{adv}. Whenever an agent chooses a point of sale, all point of sale communication activities associated with that point of sale are executed as outlined in Algorithm 12.

Algorithm 12 Point of sale advertising

if $a_{i,k}^{prod} = 0$ **then**
  if $x = X(\overline{\omega}) < P_r^{makeAware}$ **then**
    $a_{i,k}^{prod} = 1$
    for all $(P_i, A_j, v) \in T_r^{adv}$ **do**
      if $a_{j,k}^{attr} = 0$ **then**
        $a_{j,k}^{attr} = 1$
      end if
      $\mathit{informationInflow}_k(P_i, A_j, v, w_r^{adv})$
    end for
  end if
else
  if $x = X(\overline{\omega}) < P_r^{impactAware}$ **then**
    for all $(P_i, A_j, v) \in T_r^{adv}$ **do**
      if $a_{j,k}^{attr} = 0$ **then**
        $a_{j,k}^{attr} = 1$
      end if
      $\mathit{informationInflow}_k(P_i, A_j, v, w_r^{adv})$
    end for
  end if
end if

4.4.5.2. Mass advertising events

Mass advertising events are characterized by a specific time t_r at which they occur as well as the number of consumers n_r^{reach} that are exposed. The remaining parameters are the same as for point of sale advertising activities. Mass advertising events are executed at the time t_r following algorithm 13. This algorithm first selects the n_r^{reach} consumer agents exposed to the advertisement randomly. The remainder of the algorithm then corresponds to the procedure for point of sale advertising activities. Note that a different impact parameter w_r^{adv} can be used for each mass advertising event and point of sale advertising activity.

Algorithm 13 Mass advertising

$C^{exposed} \leftarrow n_r^{reach}$ randomly chosen consumer agents from C
for all $C_i \in C^{exposed}$ **do**
    if $a_{i,k}^{prod} = 0$ **then**
        if $x = X(\overline{\omega}) < P_r^{makeAware}$ **then**
            $a_{i,k}^{prod} = 1$
            for all $(P_i, A_j, v) \in T_r^{adv}$ **do**
                if $a_{j,k}^{attr} = 0$ **then**
                    $a_{j,k}^{attr} = 1$
                end if
                $\mathit{informationInflow}_k(P_i, A_j, v, w_r^{adv})$
            end for
        end if
    else
        if $x = X(\overline{\omega}) < P_r^{impactAware}$ **then**
            for all $(P_i, A_j, v) \in T_r^{adv}$ **do**
                if $a_{j,k}^{attr} = 0$ **then**
                    $a_{j,k}^{attr} = 1$
                end if
                $\mathit{informationInflow}_k(P_i, A_j, v, w_r^{adv})$
            end for
        end if
    end if
end for

5. Model Implementation and Testing

5.1. Tools for implementing agent-based simulations

In recent years, the incursion of agent-based modeling in many scientific disciplines has entailed the development of increasingly sophisticated software-platforms for agent-based modeling and simulation. Today, a modeler selecting a platform for the implementation of an agent-based model is therefore faced with an abundant range of programming languages, libraries, frameworks, and modeling environments to choose from. In this section, we briefly outline some of the available options.

Programming languages At the most basic level, it is feasible to implement agent-based models with "plain" general purpose programming languages rather than relying on specialized software tools. Early agent-based models were typically implemented independently following this approach (Gilbert, 2002a). Today, implementing the whole simulation "from scratch" still appears to be a relatively common approach, even though it leads to duplication of efforts because it forces modelers working on different models to repeatedly implement basic algorithms. This process is error-prone, may lead to code that is not easily accessible, and impedes verification of the implementation. Typically, object-oriented languages such as Java or C++ are used because core concepts like encapsulation, inheritance, and abstraction fit the agent-based modeling paradigm well. Types of agents are implemented as classes, particular agents are instances (i.e., objects) of these classes that have an internal state, and agents' interactions with one another and their environment are implemented as methods of the agent classes.

Other, somewhat less common approaches, are to build agent-based simulations on top of computational mathematics systems such as Mathematica (Wolfram Inc., 2011) or Matlab (MathWorks, 2011), procedural languages (e.g., StarLogo, cf. Resnick, 1996), functional languages (Legéndi et al., 2009), or spreadsheet software (Macal and North, 2007).

Libraries and toolkits Specialized libraries and toolkits that provide dedicated facilities for agent-based simulation offer modelers a number of significant advantages over implementing a model "from scratch". First, they provide standard mechanisms and algorithms that implement functionality that is frequently required in agent-based modeling, such as scheduling, event handling, random number generation, network modeling, logging, visualization, and analysis.

As a consequence, the resulting code can be more compact, accessible and easier to verify than custom implementations that involve large amounts of “boilerplate” code. By providing ready-made building blocks, standardized libraries can assist modelers and ideally save them time, effort, and energy.

Modeling environments While libraries may assist modelers with only limited programming skills, they still require sufficient fluency in the underlying programming language. Modeling environments, by contrast, provide an entire graphical model building interface and allow modelers to assemble building blocks visually or with very limited syntax. They may therefore alleviate this problem or require no programming at all. Such environments include, for example StarLogo (`http://education.mit.edu/starlogo/`), NetLogo (`http://ccl.northwestern.edu/netlogo/`), Repast S (`http://repast.sourceforge.net/`), Eclipse Agent Modeling Framework (`http://www.eclipse.org/amp/`), and Anylogic (`http://www.xjtek.com/anylogic/`). The main disadvantage of complete modeling environments is that they may impose assumptions upon the model and limit the modeler’s ability to control detailed aspects of the simulation.

Several authors have reviewed available libraries and environments for agent-based simulation. In an early survey, Gilbert (2002a) provide a brief overview of the toolkits available at that time and compare the state of development of software tools for agent-based simulation to the early stages of development of statistical software. Tobias and Hofmann (2004) evaluate free Java-libraries for social agent-based simulation, comparing 19 different characteristics across the four platforms evaluated, and conclude that the Repast environment (North et al., 2006) was the most advanced of the libraries at the time of the review. Railsback et al. (2006) review four main platforms (NetLogo, Mason, Repast, Swarm) and compare them by implementing a template “StupidModel” at various levels of sophistication in each of them. In total, they discuss sixteen intentionally simplified template models, and provide full specifications for all of them. Isaac (2010) refine these template models and provide implementations in Python, which they find are highly readable and more compact than implementations in other languages. Castle and Crooks (2006) examine eight simulation platforms, focusing particularly on evaluating geospatial capabilities. The most extensive survey to date was conducted by Nikolai and Madey (2009). The authors compare five characteristics of 53 toolkits, viz. programming language, operating system support, type of license, primary domain for which the toolkit is intended, and types of support available to the user.

Many powerful tools are available to the model builder today and for this research, a number of options were considered. Table 5.1 provides an overview of selected frameworks considered as a platform for the implementation of the proposed model.

Platform	Web Site	Language	License	Reviewed in
AnyLogic (Garifullin et al., 2007)	`http://www.xjtek.com/`	UML-RT; Java	proprietary	Castle and Crooks (2006); Nikolai and Madey (2009)
Ascape (Parker, 2001; Inchiosa, 2002)	`http://ascape.sourceforge.net/`	Java	BSD	Gilbert (2002a); Nikolai and Madey (2009)
MASON (Luke et al., 2004)	`http://www.cs.gmu.edu/~eclab/projects/mason/`	Java	Academic free, open source	Castle and Crooks (2006); Railsback et al. (2006); Nikolai and Madey (2009)
NetLogo (Tisue and Wilensky, 2004)	`http://ccl.northwestern.edu/netlogo/`	NetLogo language	free, not open source	Castle and Crooks (2006); Railsback et al. (2006); Nikolai and Madey (2009)
RePast (v1–3) (North et al., 2006)	`http://repast.sourceforge.net/repast_3/index.html`	Java (RepastJ), Python (RepastPy), C++, .net (Repast.net: C#, J#, VB.net etc.)	BSD	Gilbert (2002a); Tobias and Hofmann (2004); Castle and Crooks (2006); Railsback et al. (2006); Nikolai and Madey (2009)
RePast S (Howe et al., 2005)	`http://repast.sourceforge.net/repast_simphony.html`	Java, Groovy	BSD	Nikolai and Madey (2009)
StarLogo	`http://education.mit.edu/starlogo/`	StarLogo language	free, not open source	Gilbert (2002a); Castle and Crooks (2006)
Swarm (Minar et al., 1996)	`http://www.swarm.org`	Objective C, Java	GPL	Gilbert (2002a); Tobias and Hofmann (2004); Castle and Crooks (2006); Railsback et al. (2006); Nikolai and Madey (2009)

Table 5.1.: Selected agent-based simulation frameworks

5.2. Platform and tools used in the implementation

A number of criteria were considered in the selection of tools for the implementation of the proposed model. First, because the simulation was deployed on a high-performance computing cluster, a platform-independent implementation that could be run on various operating systems (Windows, Mac OS X, Linux) was required. Java-based frameworks have significant advantages in this respect, because the resulting simulation program is portable and can easily be deployed on any computing platform without recompiling the code. Furthermore, the simulation returns consistent results independent of the underlying computing architecture, which is by no means a matter of course when natively compiled code is used. Moreover, almost any of the available Java-based agent-based simulation frameworks can be easily complemented with any of the wide array of software libraries available for the Java programming language. Since Java is the main programming language most frameworks have adopted (42% of the frameworks reviewed by Nikolai and Madey, 2009), the number of available options that fulfill this requirement is large.

Second, the continuous time approach we chose for our model requires appropriate discrete event scheduling mechanisms, i.e., means for maintaining and processing a list of scheduled events. Because most frameworks are based on a discrete time approach and unfold their full potential only in a discrete time setting, the number of candidate platforms was significantly reduced.

From the remaining options, we finally chose MASON (Luke et al., 2004), a fast discrete-event multiagent simulation core written in Java that also provides a fast Mersenne Twister (Matsumoto and Nishimura, 1998) implementation for pseudo-random number generation. MASON is open source, lightweight, and can be run without a graphical user interface or visualization on a headless server. It also provides checkpointing capabilities and allows for simulation runs to be dynamically migrated across platforms.

The simulation was implemented in Java SE6 using several additional libraries and tools which are summarized in Table 5.2. The list includes a number of commonly used standard tools, specialized Java libraries that provide functionality required in the simulation, and standard tools for statistical analysis of results and automation of the simulation process.

Basic Java tools The first group of tools used consists of Apache Maven, Commons and Log4j, XStream and jUnit. Apache Maven was used to manage builds and dependencies of the various Java libraries used in the implementation. Verification of micro-level mechanisms is crucial in agent-based simulations, since implementation errors cannot be easily detected and traced in the simulation's emergent macro-level output. We therefore conducted extensive unit tests of major model mechanisms using jUnit on the micro-level. Apache Commons (Log4j) was used to log simulation events. The recording of detailed information results in the generation of a considerable amount of data. Therefore, a flexible logging facility that provides mechanisms to

Component	Website	Purpose
Java SE6	`http://java.sun.com/`	implementation of the simulation
MASON	`http://www.cs.gmu.edu/~eclab/projects/mason/`	agent-based simulation core
Apache Maven	`http://maven.apache.org/`	build management
jUnit	`http://www.junit.org/`	unit and integration testing
CERN Colt library	`http://acs.lbl.gov/software/colt/`	probability distributions, statistics
JUNG framework	`http://jung.sourceforge.net/`	(social) network generation and visualization
GeoTools GIS toolkit	`http://geotools.codehaus.org/`	geospatial model, shapefile reading, distance calculations
Apache Commons, Log4j	`http://www.apache.org/`	utility classes; logging of output and simulation results
XStream	`http://xstream.codehaus.org/`	XML deserialization for parameter and configuration files
Perl	`http://www.perl.org/`	automation of parameter sweeps and analysis process
GNU R	`http://www.r-project.org/`	analysis of results; graphs

Table 5.2.: Platform, libraries and tools used in the implementation

selectively activate or deactivate output at runtime and that is executed in a separate thread that is independent of the main simulation program can provide significant performance benefits (particularly on multi-core computers). Log4j was used to produce both comma separated output for analysis and an optional human readable textual log files. Finally, we aimed for a highly generic and versatile simulation that is fully configurable at runtime. To this end, all model input and the configuration of parameters can be performed by means of various human-readable XML files. XStream, a fast XML serializer and deserializer, was used to read these XML files into the simulation.

Specialized libraries A number of specialized libraries were used to implement particular aspects of the model. First, the model incorporates probability distributions in many places. The Cern Colt library (in particular, functionality provided in the `cern.jet` package) was therefore a valuable resource that allowed for a very generic implementation without "hardcoding" any distributions in the code. The resulting simulation tool allows modelers to select from various types of distributions for specific simulation scenarios at runtime through configuration of XML parameter files. Next, the Java Universal Network/Graph Framework (JUNG) was used for visualizing, reading, writing, and analyzing the social networks used in the simulation. Implementations of some of the generative network algorithms discussed in Subsection 4.3.5 are also provided by this library. Finally, we used geotools GIS toolkit to implement the geospatial model and read data in ESRI shapefile format.

Tools for analysis and automation Gnu R was used extensively to analyze and plot data. Bash and Perl scripts were used to automate the simulation process, discretization of data, and analysis and plotting of results.

5.3. Architecture of the software implementation

Major design objectives for the implementation of the simulation included:

- Reproducible results
- Provision of a flexible parameterization mechanism
- No "hardcoding" of parameter values in the program code
- Scalability and support for parallelization

The first objective was achieved by initializing the random number generators in the simulation with random seeds from a configuration file. Integration tests were performed regularly during the implementation process to ensure that the same parameter set simulated with the same seed always yields identical results.

The second and third objectives were achieved by implementing a convenient parameterization mechanism based on a number of separate XML files to configure various aspects of the model (cf. the following section for details). Major advantages of this method are that the parameter files are human-readable, can be easily edited, and that they can be validated against XML Schemas (XSD). The partitioning into separate files allows for their reuse in multiple scenarios and avoids redundancy. To simulate the diffusion of an innovation at varying price levels, for example, the same set of parameter files can be used for all price levels, with the sole exception of the pricing policy file. A single line that points to the pricing policy to use in the simulation has to be edited in a configuration file that binds the parameter set together (`run.xml`). The left-hand side of Figure 5.1 illustrates the configuration files and their relations.

The fourth objective was achieved by dividing the steps in the simulation process into distinct program modules. Rather than optimizing for parallelization within individual replications (i.e., use of multiple processing cores to process events in a simulation run), we designed the simulation tool so that a set of runs with varying random seeds can be performed in parallel on multiple cores or computing nodes and results can then easily be collected, aggregated, and analyzed in a separate step. In particular, the following four distinct steps are performed for each simulation scenario, as illustrated in Figure 5.1:

1. Modeling of the scenario to simulate in a number of configuration files
2. Simulation of the scenario for the number of replications specified
3. Discretization and aggregation of results of individual simulation runs
4. Plotting and analysis of results

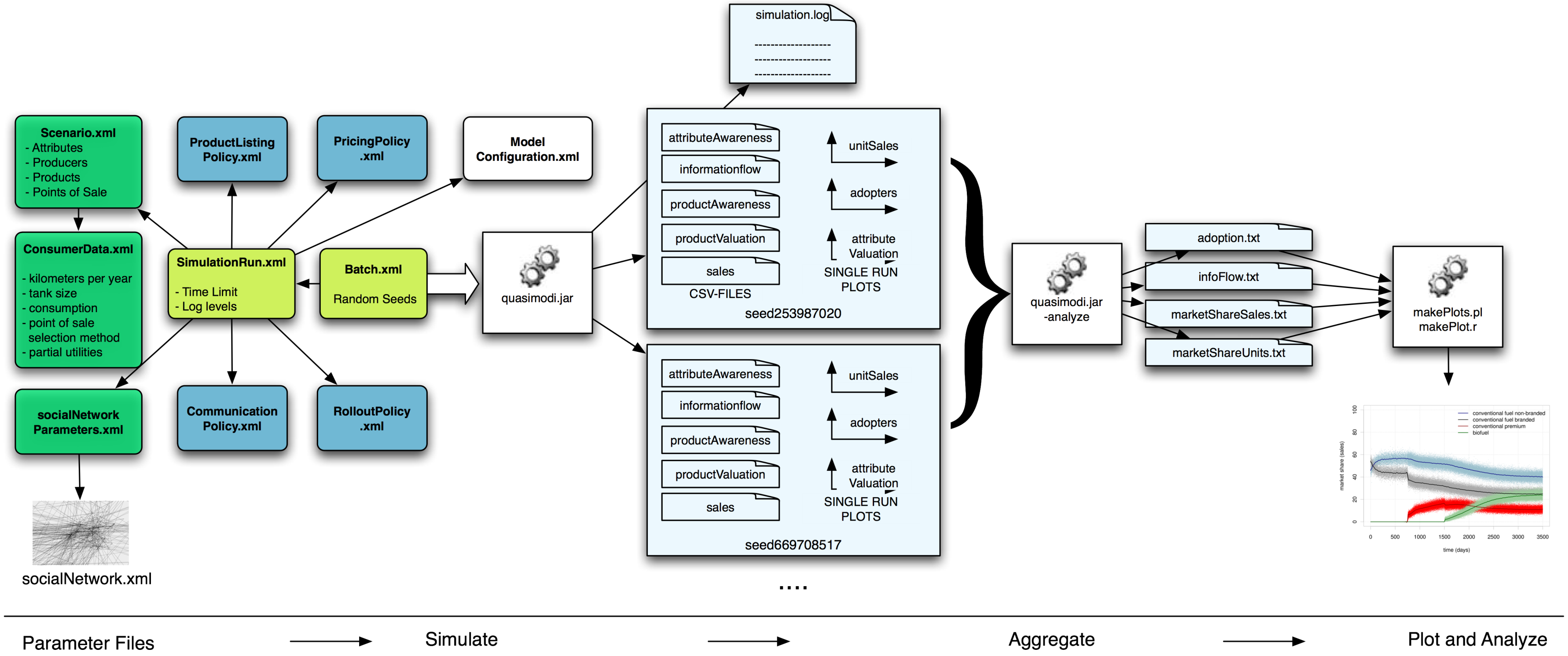


Figure 5.1.: Architecture of the software implementation

5.4. Parameterization mechanism

Each simulation job is specified in a set of XML files that follow specified formats and can be validated against XML Schemata (XSD). Arbitrary file names can be chosen for these files, as long as the reference in `run.xml` is correct. The relations between these parameter files are illustrated in the left part of Figure 5.1. The following XML files are used to specify parameters:

1. `ModelConfiguration.xml`: configuration of model mechanisms
   - Communication model
   - Topic selection mechanism
   - Product evaluation model
   - Agent initialization method
2. **Run files:**
   - `Batch.xml`: random seeds
   - `SimulationRun.xml`:
     - Time limit
     - Logging configuration
     - References to all other configuration files
3. **Scenario specification:**
   - `Scenario.xml`:
     - Product attributes
     - Producers and products
     - Number of consumer agents
     - Utility function parameters (for each attribute: monotonous, increasing?)
     - Product information model (information decay factor, number of histogram bins)
     - Communication parameters (communication interarrival time distribution, number of topics per communication event distribution, credibility distribution)
     - Initial product awareness (for all products)
     - Initial attribute awareness (for all attributes)
     - Initial attribute valuations (for all product attributes)
     - Marketing communication impact factors
     - Points of sale (id, name, location, attraction, brand, markup)
     - Geography shape file name and population field name
   - `ConsumerData.xml`: individual-level empirical data for each respondent:
     - Kilometers per year
     - Tank size
     - Consumption
     - Point of sale selection method and parameters

    - Partial utilities
  - `socialNetworkParameters.xml`:
    - Social network generation parameters or
    - Pointer to social network file

4. **Strategy specification:**
  - `PricingPolicy.xml`:
    Set of price change events (product, time, price)
  - `RolloutPolicy.xml`:
    rollout events for all products (product, time, point of sales)
  - `ProductListingPolicy.xml`:
    point of sale policies (product, starting time, interval, minUnitShare, noTimesFail)
  - `CommunicationPolicy.xml`:
    communication activities (product, time, attribute values, # agents reached)

Example configuration files for the application case introduced in Chapter 6 are included in Section A.2.

6. Biofuel Application

In this chapter, we discuss a particularly interesting application of the model introduced in the previous section. We study the diffusion of a novel second generation biofuel at the Austrian market, investigate whether or not and how fast this innovation may be adopted by consumers, and demonstrate how the model can be used to analyze strategies for the market introduction of such a product.

6.1. Background: Biofuels

Concerns over the long-term supply of fossil fuels in the face of declining oil reserves, sustained high energy prices, and many countries' critical dependence on oil imports have fueled interest in alternatives to fossil energy sources. In addition to these economic considerations, and perhaps even more importantly, the severe environmental impact of fossil fuel use has also increasingly become evident and acknowledged in recent years. This has increased the level of government support for a transition to less harmful and more sustainable energy sources.

The transportation sector is second only to the industrial sector in terms of total end-use energy consumption. Almost 30 percent of the worlds total delivered energy is used for transportation, most of it in the form of petroleum-based liquid fuels (EIA, 2010). In the long run, hydrogen-powered, plug-in hybrid, and electric cars may provide low-carbon alternatives, if (and only if) centralized production of hydrogen and electricity are decarbonized. At present, however, hydrogen production methods are still inefficient, and some have a worse carbon footprint than petroleum-derived fuels (Gomez et al., 2008). Moreover, in the short run substitutes for fossil fuels have to ensure full compatibility with the existing infrastructure in order to have the potential to become adopted by a significant share of consumers. The need for such alternatives has spurred research on transportation fuels from renewable resources.

The quest for more sustainable and environmentally benign sources of energy has become particularly pressing because the burning of fossil fuels is a large contributor to increasing the level of greenhouse gases (GHGs) in the atmosphere. Increasing concentrations of GHGs in the atmosphere are in turn linked directly to global warming observed in recent decades (Alley et al., 2007). This anthropogenic influence on climate change is now generally accepted by most authorities working in the area of climate studies, as well as most creditable politicians (Gomez et al., 2008), as reflected most recently in the acknowledgment by the Copenhagen Accord that GHG emissions have to be reduced drastically to mitigate climate change and limit global warming to 2 °C (United Nations Conference of the Parties, 2009). To preserve the technical feasibility of a 50% likelihood of keeping global average temperate at 2 °C above preindustrial in 2100, global emissions must be reduced by about 20% below 2000 levels by 2050 (O'Neill et al., 2010).

Road transportation accounts for a large and fast growing share of GHG emissions. In industrial countries, liquid transportation fuels account for approximately 30% of carbon emissions (Gomez et al., 2008); in the EU, more than 20% of net CO_2 emissions originate from the transportation sector (EEA, 2008, 2009). Transportation is therefore a major target in the drive to cut carbon emissions and climate change policy objectives cannot be achieved without intense efforts in this sector. This has been politically acknowledged in the EU Renewable Energy Directive (European Commission, 2009), which mandates a 10% renewable energy target for the EU transport sector by 2020[1] (cf. Lonza et al., 2011). In the US, the Energy Policy Act (U.S. Congress, 2005) also encourages the use of agriculture-based fuels (ethanol and biodiesel) in the transportation sector. However, first generation biofuels available today have been criticized on the grounds of being ineffective (e.g., Kutas et al., 2007) and on ecological grounds, as we will discuss in the following section.

6.1.1. First generation biofuels

Partly driven by political objectives, first generation biofuels — biodiesel (bioesters), bioethanol and biogas — have reached a commercial scale today, with almost 50 billion liters produced annually (Naik et al., 2010). These agriculture-based fuels can either be blended with petroleum-based fuels and combusted in existing internal combustion engines or used in alternative flexible fuel vehicles (ibid.). They are typically produced from starch or vegetable oil obtained from food crops (e.g., grains, corn, rape, or sunflowers) and provide a potentially carbon-neutral or at least low-carbon energy source if the CO_2 released in their combustion equals the CO_2 tied up by the plants they are produced from during photosynthesis. However, the agricultural production of these fuels is associated with a number of severe environmental concerns.

First, growing sugar and starch crops usually involves large quantities of pesticides and nitrogen-based fertilizers. These fertilizers generate nitrogen oxides, which are harmful GHGs whose emission can outweigh any potential CO_2 savings (Hill et al., 2006; Inderwildi and King, 2009).

Second, whether biofuels offer carbon savings depends on where the feedstocks used for their production are grown. If new biofuel feedstock plantations are created, CO_2 emissions caused

[1] With respect to total energy used in electricity, heat and transportation sectors, the directive requires EU Governments to increase the share of renewable energy to 20%.

by the land-use change as well as the removal of a carbon sink create a debt which has to be paid back by the biofuel; in the case of palm tree plantations created by deforestation of peatland rain forest, for example, it would take an estimated 423 years before actual carbon savings can be realized (Fargione et al., 2008). The EU Renewable Energy Directive does not require that CO_2 emissions from the indirect land-use impacts of biofuels be taken into account, but only "requests" the European Commission to put forward proposals that would limit these impacts.

Third, a negative net energy return has been reported for various first generation biofuels, indicating that their (subsidized) production may require an overall fossil energy input that exceeds the energy output of the biofuels produced (Pimentel and Patzek, 2005).

Finally, agricultural production may negatively impact water resources (Logan, 2008), increase soil erosion, and threaten biodiversity (Inderwildi and King, 2009). Aside from these environmental concerns, the increased competition for land and the diversion of grain away from food to fuel production also puts pressure on the global food market and exacerbates food security issues in the developing world (Odling-Smee, 2007; Inderwildi and King, 2009).

6.1.2. Second generation biofuels

For the reasons outlined in the previous section, the focus of research has shifted to second generation biofuels that can be produced more sustainably from lignocellulosic resources including nonfood materials available from plants, dedicated non-food biomass crops, or non-food parts of edible crops. More specifically, potential feedstocks include short rotation forestry crops (poplar, willow and eucalyptus), perennial grasses (miscanthus, switch grass and reed canary grass) and residues from the wood industry, forestry and from agriculture (Naik et al., 2010). These synthetic fuels avoid many of the issues related to first generation biofuels and can be truly carbon neutral or even carbon negative in terms of their impact on CO_2 concentrations (Naik et al., 2010).

Second generation biofuels can be produced from biomass by means of various biomass-to-liquid (BtL) conversion processes. For a comprehensive overview of first and second generation biofuel production processes, we refer to Gomez et al. (2008) and Naik et al. (2010). A particularly promising approach is the thermochemical BtL route through gasification, which can essentially convert all the organic components of the biomass. Biochemical processing, by contrast, focuses mostly on the polysaccharides (Gomez et al., 2008). For transportation fuels, the main syngas derived routes to fuels are hydrogen by water-gas-shift reaction, hydrocarbons by Fischer-Tropsch (FT) synthesis or methanol synthesis followed by further reaction to produce hydrocarbon or oxygenerated liquid fuels (Naik et al., 2010). At present, the production of second generation biofuels is not cost-effective and the technology to produce them is still under development. While a number of technical barriers still remain, they are expected to be overcome in the near future.

6.2. Application case "BioFiT"

The present application case is concerned with the diffusion of "BioFiT", a second generation biofuel that is currently under development at the Institute of Chemical Engineering at the Vienna University of Technology (cf. Fürnsinn, 2007). The production of this BtL fuel is based on gasification and subsequent Fischer-Tropsch synthesis. FT synthesis, which converts a CO and H_2 mixture into liquid fuels or hydrocarbons, has been in use since the 1930s (Schulz, 1999). Today, it is mainly used for the production of synthetic fuels from coal. Recent years have seen renewed interest in the technology as a route for gasification-based production of synthetic fuels from biomass. In particular, the resulting fuels are considered a promising carbon neutral alternative to petroleum-derived fuels that are likely to be cleaner, having essentially zero sulfur and other contaminants and low aromatic content (Liu et al., 2011). Amongst others, the product distribution obtained from FT synthesis includes both gasoline (C_5-C_{12}) and diesel fuel (C_{13}-C_{22}) (Naik et al., 2010).

At present, the application case biofuel is produced on a laboratory scale in a pilot plant in Güssing, Austria (Hofbauer et al., 2005) in co-production with domestic heating and electricity[2]; industrial scale up and market introduction are expected within the following five years. The fuel product obtained from the process (i) is fully compatible with the existing infrastructure, (ii) mixable with conventional fuels without any restrictions, and (iii) offers superior combustion properties and extremely low sulphur-contents, leading to enhanced engine performance and lower emissions.

While no investments are required on the consumer side, producers need to invest in biorefineries to start production. These biorefineries would also work efficiently on a relatively small scale and, thus, could be set up geographically dispersed near abundant sources of biomass, thereby further reducing transport distances. However, even for the smaller biorefineries, large amounts of resources are still at stake. Therefore, investors seek support in investigating the risks and market opportunities of such a product as well as in developing and testing strategies for market introduction. In this chapter, we demonstrate how an implementation of the model introduced in Chapter 4 can provide such support.

6.2.1. Scope and modeling assumptions

The diffusion model introduced in Chapter 4 simulates the behavior of individuals acting on their own and making decisions autonomously; accordingly, we exclude organizational buying from consideration in the present application case and limit our analysis to individual private buying decisions.

Furthermore, we assume that the novel biofuel is marketed as an independent "premium"

[2] From an economic perspective, co-production is a particularly interesting approach, cf. Liu et al. (2011).

product rather than being blended with conventional gasoline or diesel. The latter approach is currently common practice in many areas of the world where conventional fuels are blended with first generation biofuels (bioethanol, biodiesel). In Brazil, various US states, and many EU Member States (Sautter et al., 2007; Kutas et al., 2007; Balat and Balat, 2009), for example, blending of conventional fuels with ethanol[3] has been subsidised, granted tax concessions, or mandated. In the EU, individual Member States are free to decide upon the most appropriate way to achieve the ten percent binding minimum target for renewable sources in the transportation sector by 2020 mandated by the Renewable Energy Directive (European Commission, 2009). Some of them have adopted mandatory blending requirements in order to achieve this target. The second generation biofuel in our application case will not be cost-competitive initially, but will offer superior characteristics comparable to today’s “premium” fuels. Positioning “BioFiT” as a separate high-quality product similar to existing premium fuels, with the added benefit of being produced from sustainable resources, therefore appears to be the most likely course of action for an investor. Note that because the product is perfectly mixable with conventional fuel and fully compatible with the existing infrastructure, no technical barriers to adoption exist.

Next, it is assumed that once a need for fuel arises, it is always satisfied by consumers by choosing a gas station and selecting one of the available fuels based on available information on its characteristics and price. In other words, we assume that consumers do not follow “strategic refueling behavior” over time by waiting for prices to fall or refueling a partly emptied tank because prices have fallen.

Given the relative inelasticity of short-term fuel demand, it is also reasonable to assume that variations in price do not cause immediate changes in consumers’ mobility behavior (for a discussion and review, cf. Goodwin et al., 2009) or purchase of new cars. Because we are interested in modeling consumers’ fuel purchasing behavior during the introduction of a new fuel product and our simulation covers only a limited time frame, we assume that the car fleet remains static over the simulation period. Consumer choice of new passenger cars and the long-term changes in fuel demand due to changes in the car fleet are beyond the scope of our modeling efforts and have been the subject of other authors’ investigations (cf. the agent-based models developed by Schwoon, 2006; Kieckhäfer et al., 2009; Mueller and de Haan, 2009; de Haan et al., 2009; Kim et al., 2011; Zhang et al., 2011).

Finally, we do not distinguish between diesel and gasoline fuel types in our simulation experiments. For the sake of simplicity, we also do not distinguish between fuel products based on their octane rating. Furthermore, we assume that both fuel types have a constant market potential in the short and medium run due to technical requirements of the existing car fleet. Whereas in principle, various fuel types can be produced from syngas, we assume that only a single second generation biofuel product will be produced after initial investments have been

[3] In various concentrations such as E5, E10, E30, where the number indicates the percentage of ethanol.

made and simulate its spread in the potential market (i.e., consumers of the respective fuel type).

6.2.2. Model extensions required

To account for a number of distinct features of the specific application case at hand, some minor extensions to the generic model introduced in Chapter 4 are necessary.

Fuels To account for a specific property of fuels relevant in our model, we implemented `FuelProduct` as a subclass of `Product` from which it inherits attributes and behavior. While some fuel products such as bioethanol have a lower energy content than conventional fuels and therefore achieve a lower range, synthetic biofuels may achieve a higher range per tank filling than conventional fuels. Fuel products are hence characterized by an additional attribute "base range multiplier" that is applied to the range of consumers' cars to calculate the actual range when determining the timing of the next fuel stop.

Fuel consumer agents To account for consumers' heterogeneity in terms of mobility behavior, we implemented a specialized class `FuelConsumerAgent` which inherits attributes and behavior of the base class `ConsumerAgent`, but incorporates three additional attributes: (i) tank size (in litres), (ii) mileage distribution (i.e., the distribution of the distance driven per time unit), and (iii) range per tank filling distribution (i.e., distribution of distance driven between fuel stops in kilometers). Arbitrary distributions can be used to describe mileage and range per tank filling. In our experiments, we assumed normally distributed values and parameterized each agent's distributions using survey data from a specific respondent.

Need event scheduling In Subsection 4.4.3, we specified that needs of individual consumer agents are scheduled according to a processes that follows an arbitrary inter-purchase distribution $G_k(t)$, for which no specific assumptions have to be made. In the extended model, need events are scheduled based on the additional attributes that characterize driving behavior. Due to the relative inelasticity of short-term fuel demand and the limited simulation horizon it is reasonable to assume that the scheduling of need events follows a stationary process. More detailed scenarios that incorporate weekly or seasonal consumption patterns could be implemented easily in the simulation, if necessary.

Purchasing process Rather than purchasing a single unit of the product, as in the base model, we assume (for the sake of simplicity) that consumers refuel as soon as they start to run out of fuel and always completely fill up their tank. The quantity purchased thus corresponds to the tank capacity of the vehicle.

Data	Source/Collection technique
Relevant product attributes	expert interviews; focus group; pre-study
Consumer preferences	conjoint experiment (online)
Mobility behavior	online survey
Communication behavior	survey; sociological study
Population distribution	Austrian census data (2001), 2.5 km raster
Gas stations	`http://www.openstreetmap.org`

Table 6.1.: Data sources and collection methods

6.3. Data collection

A potential challenge of micro-modeling approaches in general and agent-based modeling in particular is that modelers have to collect detailed data for micro-level parameterization of the model or alternatively make strong simplifying assumptions about the distribution of these parameters in the population. While this may be considered a limitation, it is also a major advantage of the micro-modeling approach because the individual-level variables postulated to determine adoption timing can be measured prior to launch (cf. Chatterjee and Eliashberg, 1990), whereas aggregate models can typically be estimated only once sufficient early adoption data has become available. In their discussion on the relation between data collection and multi-agent system design, Chattoe (2002, p. 112) also argue that despite the challenges involved, *"multi-agent systems are actually very well suited to'data driven' development because they mirror the 'agent based' nature of social interaction"*. They also discuss the potential of several data collection techniques in the context of innovation diffusion. In this section, we outline how the data collection challenge was tackled for the application case at hand by means of a diverse array of collection techniques and how we used data obtained from various sources to parameterize the model. Table 6.1 summarizes the sources and collection techniques used to obtain data for model parameterization.

6.3.1. Relevant product attributes

Potentially relevant product attributes were identified through interviews and discussion with an expert from the Vienna University of Technology, whose technological expertise was then complemented with a consumer perspective by conducting a focus group study (cf. Wilkinson, 2004). This qualitative method takes advantage of the fact that conversation can be a highly effective elicitation technique and has been suggested as a valuable data collection technique for building empirically plausible agent-based simulations (Chattoe, 2002). The relevant attributes identified in the focus group were then tested by means of a pre-study with a non-representative convenience sample of 1,000 subjects. The qualitative focus group approach was found useful as a preliminary step in the early stages of our data collection process that allowed us to thoroughly

Attribute	Levels
Quality	{ standard, premium }
Price	{ €1, 1.1, 1.2, 1.3, 1.4/litre }
Environment	{ standard, low pollution }
Brand	{ no brand, branded }
Consumption	{ standard, 5% less, 10% less }
Raw material	{ crude oil, biomass }

Table 6.2.: Conjoint analysis: attributes and levels

develop a more structured preference elicitation experiment using conjoint techniques.

6.3.2. Consumer characteristics

To ground our consumer choice model in empirical data, we conducted an online survey using a convenience sample of 1,000 subjects; this sample was representative for the general population with respect to demographic characteristics. Consumer characteristics obtained from the survey included

(i) vehicle characteristics (tank size, mileage),
(ii) mobility behavior (annual distance driven),
(iii) communication behavior (frequency of communication about cars and fuels, communication partners etc.),
(iv) point of sale selection behavior (criteria for selecting a gas station, number of gas stations used on a regular basis etc.).

To elicit individual consumer preferences, we conducted a choice-based conjoint analysis as part of the online survey. The use of conjoint methods to instantiate and calibrate agent-based models was proposed by Garcia et al. (2007), who argue that empirical conjoint data is ideal for agent-based marketing models because results are meaningful on an individual level as well as on an aggregate level. Vag (2007) also suggests that conjoint analysis and agent-based modeling may perfectly complement each other: conjoint analysis may serve as a tool that supplies static behavioral data and agent-based simulation may introduce dynamics to the static conjoint results. Zhang et al. (2011) use conjoint data to elicit heterogeneous consumer preferences and parameterize agents in a study of the diffusion of alternative fuel vehicles.

In particular, we carefully designed a conjoint experiment that involved ten paired comparisons of fuel products characterized by six attributes identified and tested in the prior steps of our research process (expert interviews, focus group, pre-study). The number of levels per attribute varied from two to five, as summarized in Table 6.2. The conjoint study measured conditional choice and therefore did not include a none-alternative (which is in line with our assumptions that in the medium run, consumers refuel their cars whenever necessary rather than changing their mobility behavior by switching to alternative modes of transportation). Figure 6.1 illustrates the distribution of part worths in the sample for each attribute and level. The results clearly show that there is considerable heterogeneity in preferences, and, not unexpectedly, that price is a very important attribute for the vast majority of consumers.

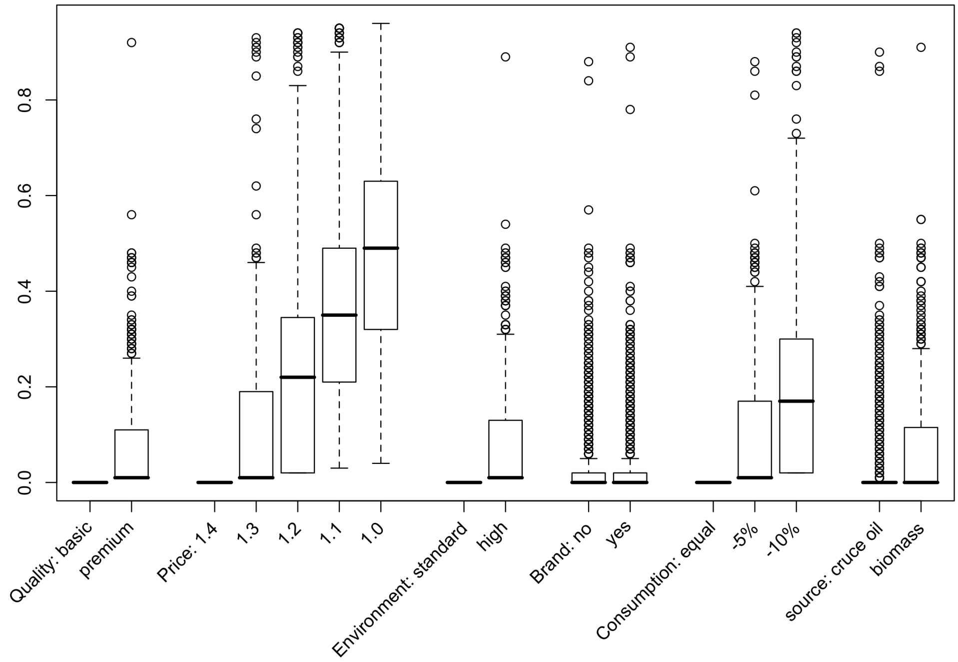


Figure 6.1.: Distribution of part worth utilities in conjoint analysis scaled in [0,1]

6.3.3. Geographic data

A number of data sources were used to create a spatial model for our simulation experiments. First, since the scope of our study is limited to the Austrian fuel market, it is necessary to establish the geographic boundaries of our model, which was accomplished by using a shapefile that contained the national borders.

Next, points of sale need to be distributed in geographic space in a realistic manner to allow for the evaluation of rollout strategies. To this end, we relied on publicly available data obtained from OpenStreetMap (`http://www.openstreetmap.org`), which as of July 2010 included the exact geographic location and operating companies of 1,571 Austrian gas stations. This data allows us to distinguish between branded and unbranded gas stations and to assign point of sale agents to actual geographic locations.

Finally, consumer agents also need to be assigned to explicit geographic locations. To this end, we used the population distribution from Austrian census data (2001) for a 2.5 km raster, which was considered sufficient for the purpose of our study.

6.3.4. Social network

To choose appropriate parameters for the spatial social network generation algorithm outlined in Subsubsection 4.3.5.4, we obtained data on consumers' product-related personal network in both our pre-study and the online survey. In particular, questions on the number of product-specific social contacts and communication frequency were included to collect data on communication behavior.

6.4. Model parameterization

Using data obtained from the various sources described in the previous section, we initialized our model by parameterizing consumer agents, setting up the spatial model, and constructing the social network in which consumer agents are embedded. This section describes the choice of model parameters as well as the rationale behind these choices.

6.4.1. Consumer agents

Number of agents The number of consumer agents ($n^{consumers} = 10{,}000$) for our simulation experiments was chosen by trading off model granularity and simulation runtime. The number chosen is large enough to allow for a realistic dispersion of agents in the geographic environment and covers not only urban, but also less densely populated areas sufficiently. We also ran simulations with a size larger by an order of magnitude ($n^{consumers} = 100{,}000$) with no significant differences in the results. For each of the $n = 1{,}000$ respondents in our online survey, we initialized ten (a priori) identical consumer agents to obtain a total number of $n^{consumers} = 10{,}000$ agents.

Preferences To account for consumers' heterogeneous preferences, we use the individual-level conjoint data to construct a piecewise linear utility function for each of the six product attributes for each respondent and parameterize consumer agents accordingly. The products in our agent-based simulation use only those attribute values that were also used as levels in the conjoint study. For the dichotomous attributes quality, brand, environment, and raw material, the interpolated attribute values between zero and one are not directly meaningful. Nevertheless, when treating agents' attribute valuations as uncertain point estimates in a continuum of beliefs, it is reasonable to assign an interpolated utility value to those beliefs. The use of interpolated utility values reflects our assumption of risk-neutral decision-makers.

Mobility behavior As noted above, we also obtained data on respondents' driving behavior which we used to parameterize fuel consumption, annual mileage, and tank size parameters of each agent accordingly.

Choice of gas station As specified in Subsection 4.4.3, our model incorporates two mechanisms for agents to choose a point of sale: either from a list of $n_k^{posHist}$ previous purchase locations with probability $p^{recentPOS}$, or randomly based on distance from home location with probability $1 - p_k^{recentPOS}$. To set the parameters $p_k^{recentPOS}$ and $n_k^{posHist}$ for each agent C_k, our empirical survey included a question that asked for the number of gas stations used by the correspondent. Possible answers included

1. *"I always use the same gas station."*
2. *"I use a few gas stations on a regular basis."*
3. *"I use a different gas station every time."*

Accordingly, we defined three parameter settings:

1. $p_k^{recentPOS} = 1$ and $n_k^{posHist} = 1$ for agents that represent consumers that always use the same gas station (269 respondents),
2. $p_k^{recentPOS} = 0.8$ and $n_k^{posHist} = 4$ for agents that represent consumers that use a few gas stations on a regular basis (612 respondents), and
3. $p_k^{recentPOS} = 0$ for agents that represent consumers that use a different gas station every time (119 respondents).

The survey also indicated that for the majority of consumers (approximately 73%), price of the fuel offered was the most important consideration when choosing a gas station (other options included additional services, convenient location, and availability of special fuel types). In light of this finding, the point of sale selection mechanism incorporated in our model, which is based on choosing a points of sale based on utility, should provide a good representation of consumers' behavior.

For the geodesic exponent used to weight the influence of the distance from the consumer agents' home location we chose $\alpha_k^{posSelect} = -5.0$. The attraction parameter was not used in our experiments (i.e., $k_l = 1 \quad \forall k \in S$). Figure 6.2 illustrates a resulting distribution of distances from the home location of an agent that chooses a different gas station every time.

6.4.2. Spatial model

Using the geographic data on population density and the location of gas stations (cf. Subsection 6.3.3), we initialize the spatial model in the following three steps: (i) distribution of gas stations according to their actual locations, (ii) distribution of consumer agents according to population density, and (iii) construction of the social network by linking consumer agents.

In the first step, we create 1,571 point of sale agents and distribute them in geographic space. Next, we create and initialize 10,000 agents and assign them to geographic locations based on Austrian population density data. More specifically, a 13,997 cell population raster with a cell

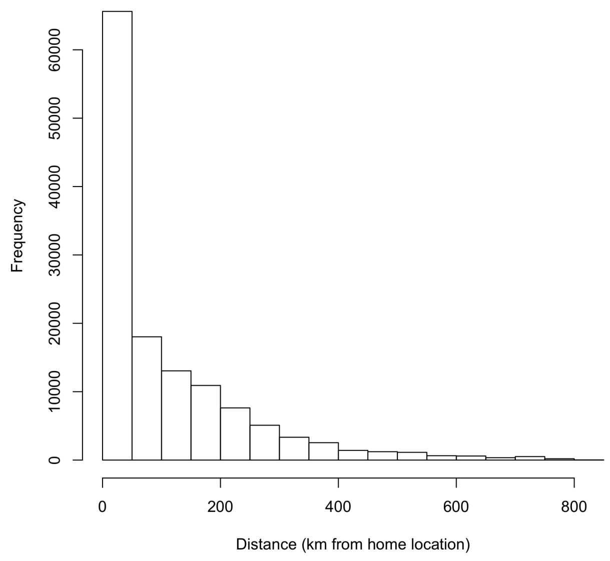


Figure 6.2.: Distribution of sales by distance from home location

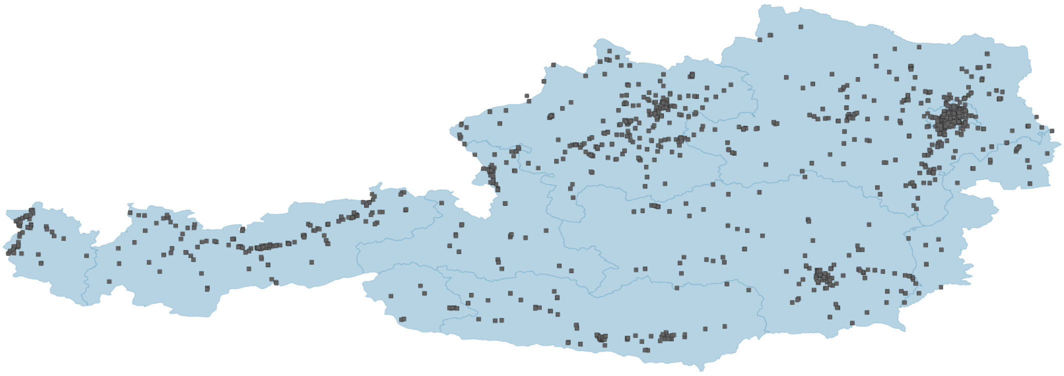
size of 2.5km was used. Agents are assigned to cells with a probability proportional to the relative share of the total population in the respective cell and positioned randomly within the target cells. Finally, consumer agents are linked in a social network as described in the following section. The individual steps of the process are illustrated in Figure 6.3.

6.4.3. Social network

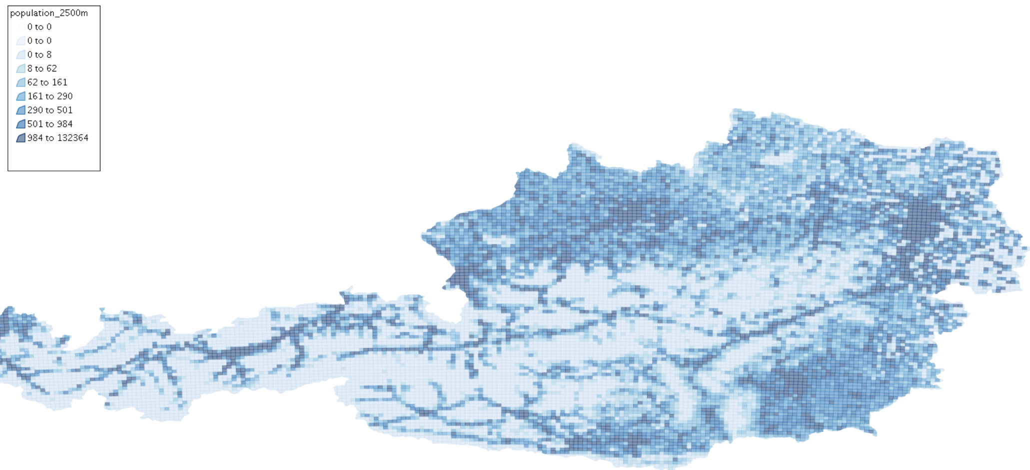
Based on information obtained in the pre-study and online survey, we chose the following values for the parameters of the spatial social network generation algorithm outlined in Subsubsection 4.3.5.4 for our simulation experiments: the distance exponent was set to $\alpha = -5$, the clustering exponent to $\beta = 1$, and set the number of edges to create per node was set to $n_{link}^{spatial} = 3$.[5] The latter parameter value is based on the average number of product-specific social contacts obtained from survey data. The exponents chosen reflect our assumptions that communication about fuels is highly localized (i.e., low α) and highly clustered, which can be achieved with a moderate value of β already.

A network instance created with these parameter settings is depicted in Figure 6.5. A detailed view of a densely populated area (Vienna region) is depicted in Figure 6.6. Summary statistics of this typical network instance are presented in Table 6.3. The average degree is the average number of edges each node has. Because we create three edges per node, the average degree is six. Density is measured as the fraction of all possible edges which are actually present in the graph. Clustering is measured by means of the clustering coefficient C (Watts and Strogatz,

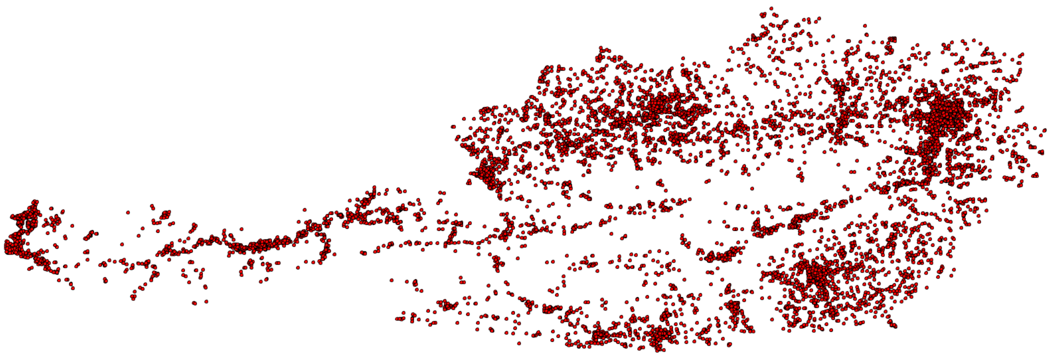
[4] Distortion is due to chosen geographic projection.
[5] More precisely, the implementation of the model allows for arbitrary distributions of $n_{link}^{spatial}$; we used $n_{link}^{spatial} \sim U(3,3)$.



(a) Distribution of 1,571 gas stations



(b) Population density



(c) Distribution of 10,000 consumer agents according to population density

Figure 6.3.: Geographic model for biofuel application[4]

Statistic	value
Average degree	6
Density	0.0006
Average shortest path	6.8013593
Average clustering coefficient C	0.4430497 ($C_{random} = 0.0006236$)
Estimated power law exponent λ	1.424591

Table 6.3.: Social network characteristics for $\alpha = -5$, $\beta = 1$, $E \sim U(3,3)$, seed=1299961164

1998) as specified in Subsubsection 3.3.2.2. We are not aware of any empirical studies that investigate the topology of interactions for our particular context that we could use to compare the characteristics of our network model to. However, the statistics indicate that the social network model used in our simulations experiments exhibits typical characteristics that are consistently reported in more general empirical studies of real-world social networks, such as high clustering and low average shortest path length. Furthermore, like in many real-world social networks, the degree distribution follows a power law, as can be seen from Figure 6.4. Using the maximum likelihood method described in Clauset et al. (2009), we estimate the scaling exponent λ by fitting $P(k) \sim k^{-\lambda}$ and find that the degree distribution approximately follows a power law with scaling parameter $\lambda = 1.424591$.

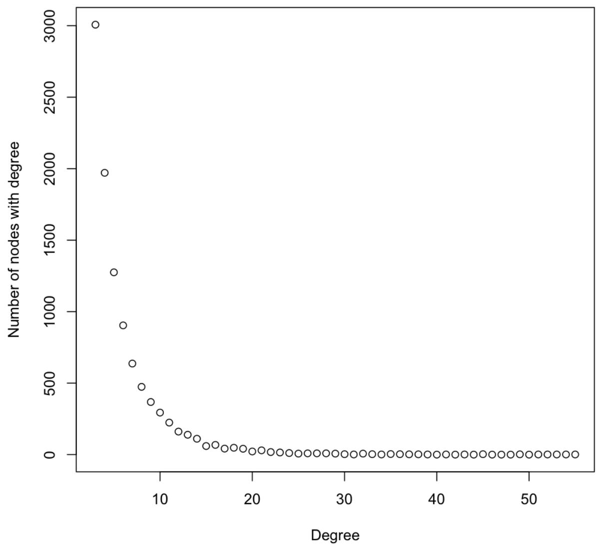


Figure 6.4.: Degree distribution of sample spatial network with parameters $\alpha = -5$, $\beta = 1$, $n_{link}^{spatial} = 3$, random seed=1299961164

6.5. Experimental Design

Before conducting simulation runs, we first carefully planned and design our simulation experiments. While the model enables decision-makers to simulate a virtually unlimited number of

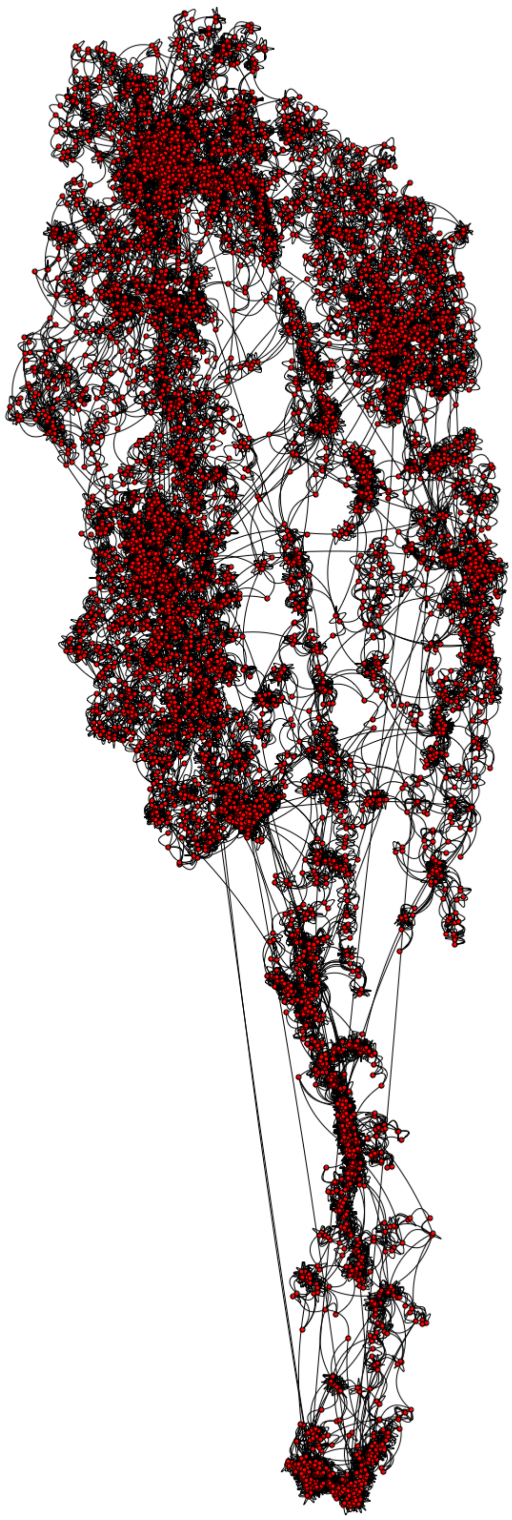


Figure 6.5.: Social network instance, $\alpha = -5$, $\beta = 1$, $n_{link}^{spatial} = 3$, seed=1299961164

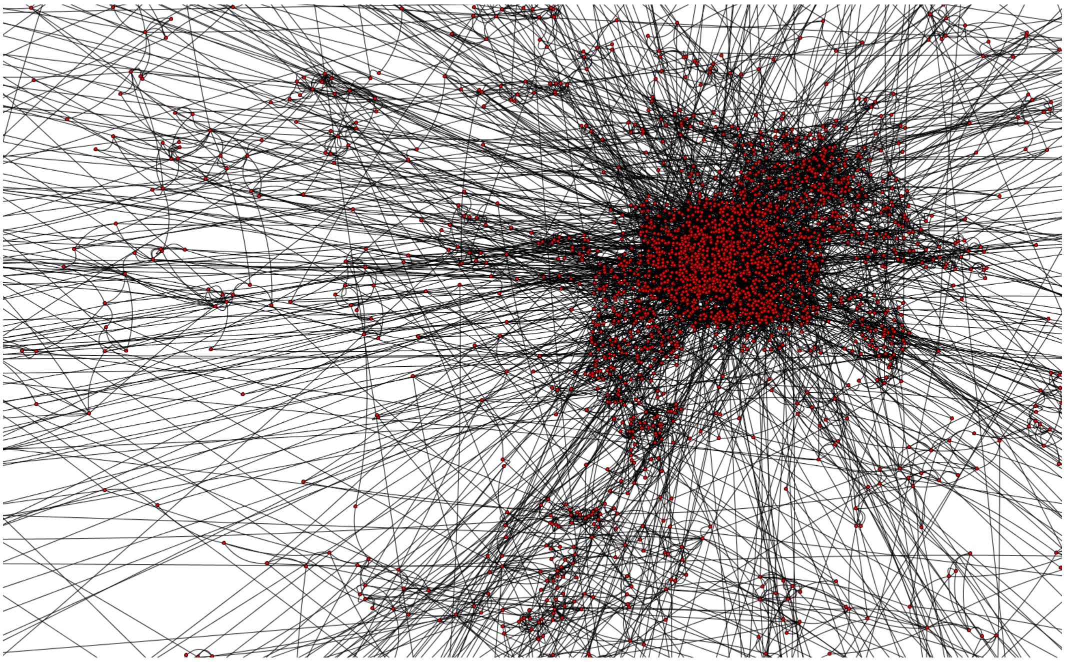


Figure 6.6.: Social network detail (Vienna region), $\alpha = -5$, $\beta = 1$, $n_{link}^{spatial} = 3$, seed=1299961164

scenarios with varying assumptions and strategic choices, we only present several illustrative cases for the purpose of this sample application. In practice, a large number of scenarios may be of interest and the simulation experiments performed will be constrained only by the available computational capacity. Since simulation runs can be parallelized easily among processing cores or clusters of networked computers, the approach scales well for more detailed investigations. In this section, we define our experimental design by addressing questions such as (i) for how long to run scenarios in simulation time, (ii) how many runs to perform for each model configuration, (iii) what measures to use for the interpretation of results, and (iv) what model configurations (scenarios) to run (cf. Kelton, 2003).

6.5.1. Time

Because the proposed agent-based model follows a discrete event modeling paradigm rather than imposing a discrete temporal structure, there is no "natural" scaling of time based on the chosen length of a period, but an arbitrary scaling of time can be chosen. In order to establish a frame of reference and facilitate interpretation of results, all parameters used were scaled so that one time unit in the simulation corresponds to one day in real time.

Moreover, there is no natural termination criterion for the simulation and a reasonable simulation horizon therefore had to be chosen based on the behavior of the system. To this end, we conducted preliminary simulation experiments to study the long-run behavior of the system and found that it converged to a steady state within 1,500 time units (i.e., approximately four years of simulation time) after the last market introduction of a product in all our tests. We chose the simulation horizon accordingly, even though this time frame is obviously relatively long in the face of growing fuel markets dynamics. While we base our simulation scenarios on the assumption that no drastic changes occur in the market, alternative assumptions such as dramatic price changes or changes in available alternatives could also be modeled easily.

6.5.2. Replications

The proposed stochastic model incorporates random numbers drawn from various distributions in various parts of the model. As described in Section 5.2, we use an implementation of the Mersenne Twister random number generator (Matsumoto and Nishimura, 1998) in our implementation. The random seeds for the various stochastic elements in the model are derived from a single random seed that determines the behavior of the system, i.e., simulation runs initialized with the same parameter setting and the same random seed always yield identical results. Because we hypothesized that the assignment of agents to geographic locations (for which no empirical data was available) may affect results, we conducted five simulation runs for each parameter setting and random seed, varying the assignment of agents to nodes in the social network in each run. To obtain information about the distribution of possible outcomes and robustness of results, we decided to perform ten replications for each parameter setting and location assignment after conducting initial experiments which indicated that the variance in simulation results was moderate. Hence, a total number of $5 \times 10 = 50$ replications per parameter setting were performed.

6.5.3. Output measures

Most models of innovation diffusion are interested only in initial adoptions over time and use cumulative or discrete adoptions over time as the relevant output measure. To study the simulation output, we also use cumulative adoptions over time as one measure, but the proposed model allows us to complement this measure with economic measures that are highly relevant from a practical perspective. In particular, the simulation allows us to also analyze the development of revenue and unit market shares over time.

Our experiments yield not a single adoption or market share curve for each product, but rather one curve for each replication. We calculate mean values that indicate the expected outcomes but also analyze the distribution of values to evaluate the robustness of results.

Because we do not track results in discrete time but only record the timing of events during the simulation, it is necessary to discretize results at the end of the process. We chose an discretization interval of one time unit (i.e., day). Hence, for each day in each replication, we count the number of adoptions and sum over sales to obtain adoption and market share curves, respectively. In addition to these primary output measures, the simulation tool can optionally generate various additional outputs that can be used to analyze individual replications in depth. These outputs include

- a human-readable logfile of simulation events (the level of detail provided is configurable),
- a product awareness chart, which exhibits the fraction of agents that are aware of each product over time,
- an attribute awareness chart, which plots the fraction of agents aware of each attribute over time,
- an information flow chart, which plots the number of communication events about specific topics over time,
- an average attribute valuation chart, which plots the agents' mean valuation of each product attribute over time (including only those agents that aware of the respective attribute),
- an average attribute utility chart, which illustrates the mean partial utility estimate for each attribute,
- an average product utility chart, which plots the mean of agents' total utility expectation for each product,
- an animation of the diffusion process, which shows the social network and consumer agents. Active communication links in the social network are highlighted and the nodes in the network change color depending on their adoption status or the last product purchased.

6.5.4. Simulation scenarios

To illustrate the capabilities of the model, we investigate the effect of a number of decision variables that are of particular interest to decision-makers planning the market-introduction of a second generation biofuel. To this end, we define a base scenario as well as a set of alternative scenarios to investigate the effect of various strategic choices on the adoption and market share development of the product. Rather than specifying a full factorial design, which would quickly become intractable given the infinite number of possible strategies, we define a number of "realistic" scenarios and strategies and manipulate key factors individually while holding everything else constant to investigate the impact of decision-makers' strategic choices.

6.5.4.1. Base scenario

Products Table 6.4 provides an overview of the products in our simulation experiments and their respective attributes values. We distinguish between non-branded and branded standard fuel, which are otherwise identical in their characteristics. Non-branded fuel is available at discount gas stations, whereas branded fuel is distributed at branded gas stations.

In our base scenario, we assume that no "premium" fuels, which are mainly characterized

Attribute	Standard non-branded	Standard branded	"Premium" fuel	BtL-fuel
Quality	standard	standard	premium	premium
Price	€ 1.2/liter	€ 1.22/liter	€ 1.35/liter	€ 1.2;1.3;1.4/liter
Environment	standard	standard	standard	low pollution
Brand	no brand	branded	branded	branded
Consumption	standard	standard	standard	5% less
Raw material	crude oil	crude oil	crude oil	biomass

Table 6.4.: Products and attribute values used in the simulation

by a higher octane (gasoline) or cetan (diesel) rating than standard fuels, are available at the beginning of the simulation. Instead, we introduce a premium fuel after the system has reached a steady state with two products. This allows us to simulate not only the diffusion of the BtL-fuel that has not yet been introduced in the market, but also that of "premium" fuels which have already diffused in the market. This in principle allows decision-makers to validate the model using data on premium fuel adoption, as discussed in Section 6.8.

Finally, the BtL-fuel is introduced at the market after the system has once again reached a steady state. Based on expert interviews, this novel fuel can be expected to exhibit performance and combustion characteristics comparable to those of premium fuels already available at gas stations today, with the additional benefit of being produced from renewable resources and being lower pollutant.

Communication strategy At the beginning of the simulation, consumer agents are not aware of the new product. In order to trigger the diffusion process, it is therefore necessary to spread awareness of the innovation among a small number of initial consumers. This is accomplished by point of sale advertising at the introduction of a new product (premium fuels at $t = 750$ and BtL-fuel at $t = 1500$). These intense point of sale advertising efforts are assumed to last for one month (30 days) and reach unaware agents with probability $P_r^{makeAware} = 0.05$ and have an impact on agents that are already aware of the advertised product with probability $P_r^{impactAware} = 0.1$ (cf. Subsection 4.4.2).

Apart from this initial "seeding" of product information, no additional advertising events are scheduled in our simulation scenarios.

Pricing strategy In the base simulation scenario, we assume static prices that remain fixed over the whole simulation. We experiment with three price levels for the biofuel to estimate the impact of price on the diffusion process. The price levels chosen for the available fuel products are based on the average price level at the time the empirical data were obtained by means of a survey and a conjoint experiments. The three price levels chosen for the BtL-fuel reflect varying assumptions about reduced production costs due to technological advances and economies of

Product	availability	time of product launch
Standard non-branded	757 discount gas stations	$t = 0$
Standard branded	814 branded gas stations	$t = 0$
"Premium" fuel	548 branded gas stations	$t = 750$
BtL-fuel	189 gas stations (major operator)	$t = 1{,}500$

Table 6.5.: Rollout in simulation scenarios

scale and/or the extent of tax breaks.

Rollout strategy In our base scenario, we assume that products are introduced at specific points of sale once and remain available until the end of the simulation. The scenario starts with only branded and non-branded standard fuel available. A premium fuel product is introduced at at 548 selected gas stations (at which premium fuels are currently available) at time $t = 750$. Finally, the BtL biofuel is introduced at every branch of a major Austrian operator at time $t = 1500$, based on the assumption of an investment in a large-scale biorefinery. Table 6.5 summarizes the timing and availability of the five products in our base scenario.

6.5.4.2. Scenario with discontinuation at points of sale

A constraint that we do not consider in the base scenario, but that plays an important role in practice, is the fact that it is not economically viable to carry the product at a gas station if it does not reach at least a certain minimum market share. If this minimum market share cannot be reached or is not maintained, investing in or maintaining a separate refueling infrastructure (gas pump, tank etc.) for the BtL-fuel may not be efficient. This clearly applies to the biofuel application case at hand, but it also applies to most other frequently purchased products because retailers will typically delist them if their sales falls short of expectations.

We assume that the decision to discontinue the new product is made individually for each point of sale. In particular, following expert suggestions, we assume that a minimum 5% unit market share is necessary to cover costs. This constraint is checked every $\Delta t = 100$ and the product is discontinued if sales are below the threshold three consecutive times. The remaining parameters and strategic choices in the base scenario remain unchanged.

6.6. Simulation results

6.6.1. Base scenario

In the base scenario, we change the price of the BtL-fuel on three levels to determine its impact on the diffusion process. For the sake of simplicity and to isolate effects, we assume that prices of all products remain fixed over the simulation.

Adoption Figure 6.7 illustrates the initial adoption curves for $p_{BtL} = 1.2/1.3/1.4$, respectively. Since the BtL-fuel is launched at t = 1,500, the plot covers only the interval from t = 1,500 to T = 3,000. The lines represent the mean results averaged over all simulation runs while the scattered points indicate adoption in individual runs. Results over 50 replications appear very robust and the adoption biofuel adoption curves exhibit the typical S-shape commonly observed in empirical diffusion studies (cf., e.g., Mahajan et al., 1995).

As can be expected, a higher price consistently results in a slower speed of adoption and a higher delay before takeoff occurs. At a price of $p_{BtL} = 1.2$, which is below that of the conventional and premium fuel products, diffusion is much faster and reaches approximately 80% of the population within the simulation horizon. Individual runs over longer simulation periods showed that adoption grows very slowly afterwards and full market penetration is not achieved within t = 5,000.

There are two reasons why a minority of consumers is largely "immune" to adoption, even when the BtL-fuel is offered at a price below that of premium fuels and hence appears to be the dominating alternative because it appears to be the "best" choice in all criteria. The first reason, which is evident from the empirical conjoint data used for parameterization, is that there are individuals that have strong preferences against fuels produced from biomass. This may be due to critical media reports on first generation biofuels and the resulting negative public perception. Second, because of the limited availability at only 189 gas stations (i.e., 12% of all gas stations) and because of the considerable number of consumer agents that use only a single (26.9% of the simulated population) or only a few gas stations (61.2% of the simulated population), not all consumer agents have the opportunity to adopt.

As expected, adoption is generally lower at higher price levels. At $p_{BtL} = 1.3$, initial adoption reaches approximately 60% of the population, and at a price $p_{BtL} = 1.4$, which is above that of premium fuels in our simulation, initial adoption reaches approximately 33% within 4 years after initial market introduction.

Sales Unlike most diffusion studies, we are not concerned with the diffusion of a consumer durable good, but rather a frequently purchased consumable product. Decision-makers may therefore be less interested in the fraction of consumers who have purchased the product at least once than in the actual market share the innovation may obtain when taking repeat purchases into account. Figure 6.8 plots unit market share of all products at each of the three price levels for the biofuel over time. Figure 6.9 provides a more detailed view on the biofuel market share development. Again, points are used to mark the results of individual simulation runs whereas lines indicate the average values. Simulation experiments over longer simulation horizons indicate that market penetration of the BtL-fuel does not increase considerably any further after t = 3,500.

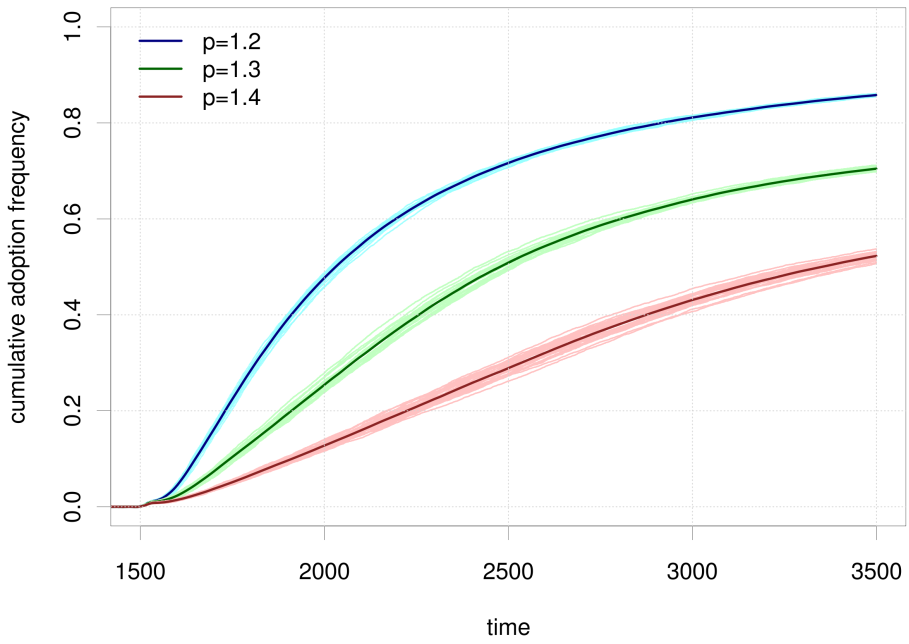


Figure 6.7.: BtL-fuel adoption for base scenario ($p_{BtL} = 1.2/1.3/1.4$)
(5 consumer assignments to nodes x 10 random seeds = 50 replications)

In the interval from the start of the simulation until $t = 750$, only branded and non-branded conventional fuel is available at the market. At the beginning of the simulation, unit market shares of branded and non-branded fuels are approximately evenly distributed. Within the first year in simulation time, however, non-branded fuels gain a significantly higher market share than branded fuels even though there are slightly more branded gas stations than unbranded ones in our simulation. In the simulation, this effect comes from consumers gaining experience and develop a preference for discount gas stations over branded ones. This result are in line with our empirical data well, because for 783 out of 1,000 respondents in our conjoint study, the lowest price (1.0) contributed the highest part worth of all attributes, whereas brand was relatively unimportant to most consumers and even had a negative effect for some of them. As expected, we therefore find that a higher price generally leads to a lower unit market share.

At $t = 750$, premium fuels are introduced at a large number of points of sale (approximately 36%) simulataneously and supported by point of sale advertising. This leads to fast initial adoption and sales growth at the beginning. Figure 6.8 also clearly shows that premium fuel sales primarily cannibalize sales fo branded fuels, because they are assumed to only be available at branded points of sale. However, a small proportion of consumers that prefer non-branded points of sale also switch to the premium fuel.

The biofuel is introduced at $t = 1500$ at 12% of the gas stations. Depending on the price level chosen, sales may grow to up to 20% (at a price of € 1.2) within one and a half year after introduction. At a more realistic price of € 1.4, the biofuel may still achieve a unit market share of approximately 8% within the same time span. At the end of the simulation, i.e., approximately four years after the biofuel's market introduction, it achieves a market share of approximately 27%/23%/18% for $p_{BtL} = 1.2/1.3/1.4$, respectively, on average.

Interestingly, as can be seen from Figure 6.8, we find that initial adopters do not purchase the novel product only once, but rather confirm their choice through experience with the product and tend to repurchase it on a continuous basis. Results also suggest that the BtL-fuel could obtain a considerable market share even at a price significantly above that of conventional fuel.

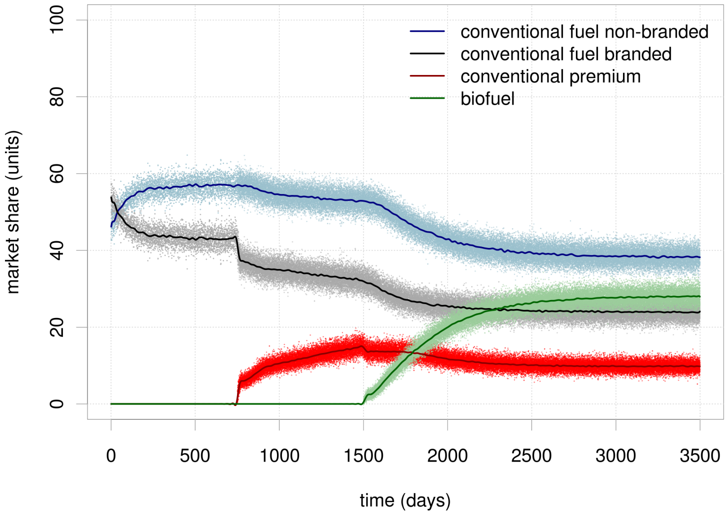
Another interesting aspect is that the introduction of the BtL-fuel at a high price level (i.e. $p_{BtL} = 1.4$) impacts the market share of premium fuels to a slightly higher degree than that of standard fuels. This is expected, since price sensitive buyers will be less likely to buy the BtL-fuel than buyers of high-priced "premium"-fuels.

Overall, results of the base scenario appear very robust despite the complexity of the model and the large number of non-deterministic elements in the simulation. While the results do not uncover any non-intuitive insights, they do support confidence in the validity of the model.

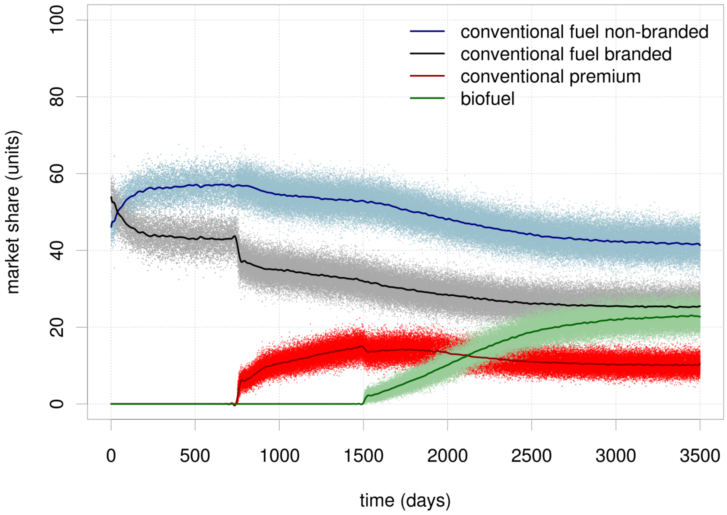
Communication In innovative aspect of the proposed model is the explicit modeling of communication content. The selection of communication topics follows the rules outlined in Subsection 4.4.2. In particular, the probability of each product attribute to be covered in a communication event depends on the change in utility estimates since the last time a pair of agents communicated. This implies that agents' preferences are an important determinant of communication topics, since attributes with no or a very low contribution in partial utility are unlikely to be included wheres important attributes for which the absolute magnitude of the same relative changes is much higher are likely to be included. Figure 6.10 illustrates the resulting content of communication across time for the base scenario (at $p_{BtL} = 1.3$) by plotting the number of communication events over time.

Communication about the standard fuel types available at the market from the beginning of the simulation is shown in Figure 6.10a and Figure 6.10b. Because the only attributes agents are assumed to be aware of at the beginning are price and brand, these are the only attributes agents talk about in a short "burst" at the beginning. More interestingly, as soon as products that differ in attributes such as quality ("premium" fuel) and consumption, environment, and raw material (Btl-fuel) become available, these topics are discussed for the existing products as well once agents become aware of these attributes. However, because existing product have an attribute value of 0 in these attributes, which corresponds to consumers' preconceptions and does not lead to a change in estimated utility, communication about these topics is short and not very intense.

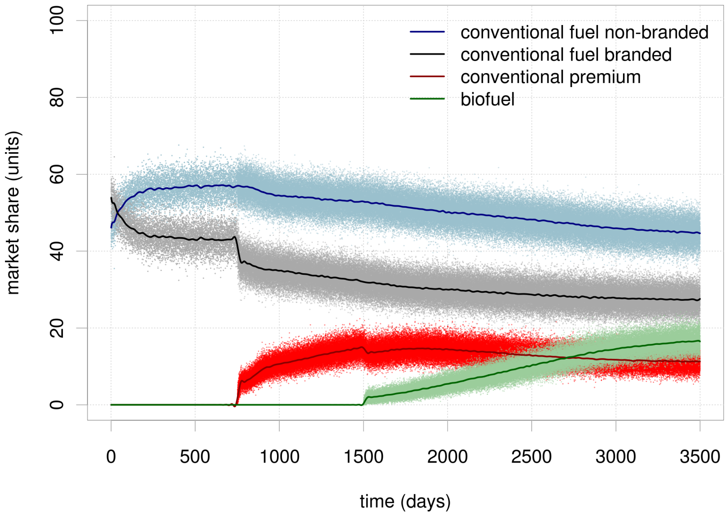
Communication about the premium fuel product introduced at $t = 750$ is illustrated in Figure 6.10c. Price, which is the most important attribute that contributes the largest partial utility



(a) Development of percentage unit market share for $p_{BtL} = 1.2$



(b) Development of percentage unit market share for $p_{BtL} = 1.3$



(c) Development of percentage unit market share for $p_{BtL} = 1.4$

Figure 6.8.: Development of percentage unit market share for base scenario ($p_{BtL} = 1.2/1.3/1.4$) (5 consumer assignments to nodes x 10 random seeds = 50 replications)

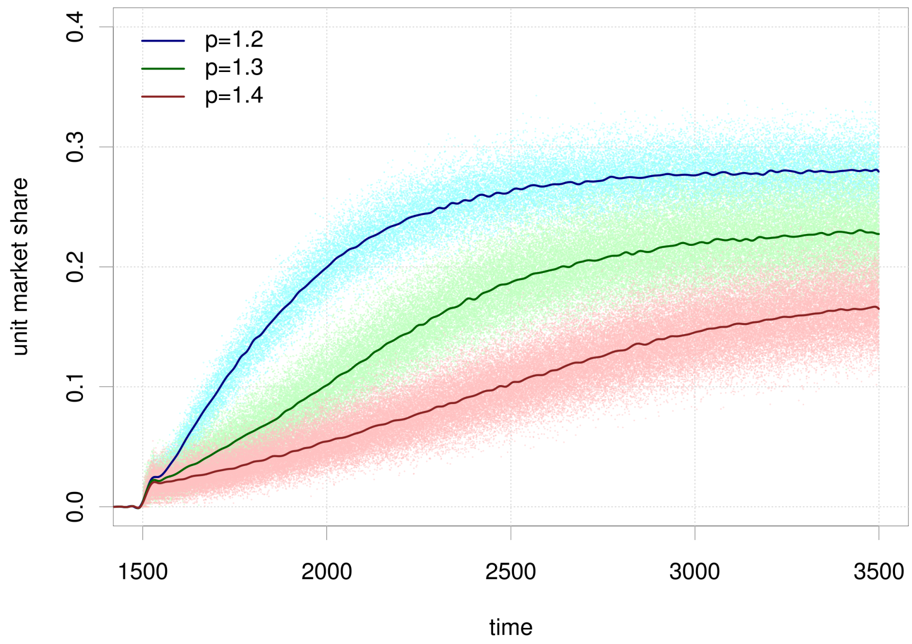


Figure 6.9.: BtL-fuel unit market share curves for base scenario ($p_{BtL} = 1.2/1.3/1.4$) (5 consumer assignments to nodes x 10 random seeds = 50 replications)

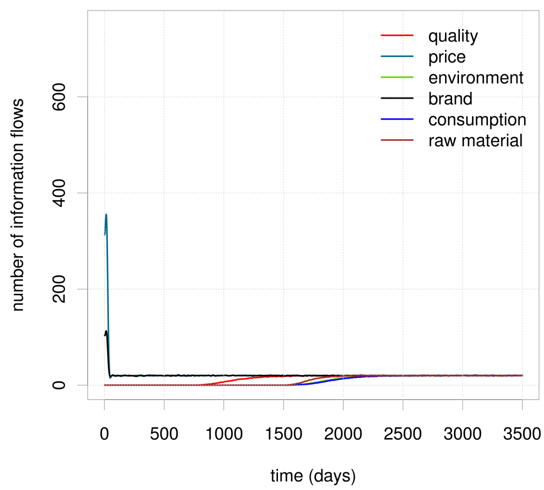
for most consumer agents, is the most intensively discussed topic, followed by brand and the new attribute quality. Brand is discussed earlier in the process because agents are already aware of that attribute. Whereas consumers rarely discuss the "brand" of a product such as fuel explicitly, this result still appears realistic in that consumers do exchange information about where a new product is available and thus, implicitly, also about its "brand".

Finally, the communication about product attributes of the novel BtL-fuel is plotted in Figure 6.10d. Again, price is the most intensively discussed aspect, followed by raw material. Brand is again discussed relatively earlier in the diffusion process because agents are already aware of that attribute. The distribution of the remaining topics quality, environment, and consumption across time are roughly similar. Plots that illustrate the communication process for price levels $p_{BtL} = 1.2$ and $p_{BtL} = 1.4$ are included in Subsection A.4.1.

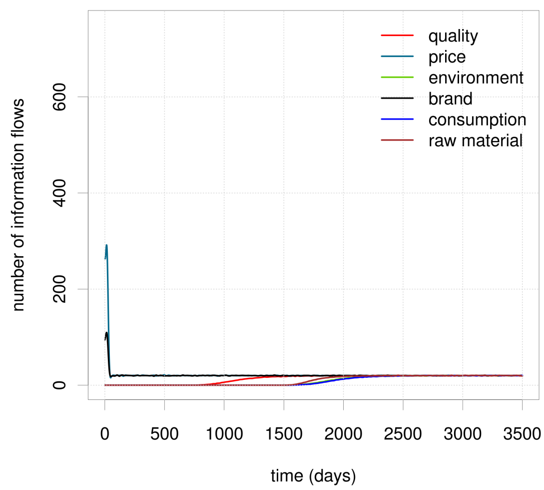
6.6.2. Scenario with discontinuation at points of sale

In the discontinuation scenario, we assume that a minimum unit market share of 5% is necessary at each point of sale to cover costs. This constraint is checked every $\Delta t = 100$ and the product is discontinued if sales are below the threshold three consecutive times (i.e., at $t = 1800$ at the earliest). Figure 6.11 plots the cumulative adoption curves for the three price levels and Figure 6.12 illustrates the development of market shares over time.

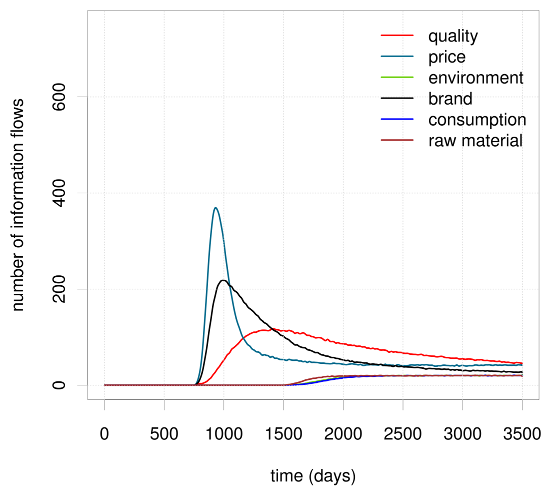
At the low price of $p_{BtL} = 1.2$, which is unlikely to be economically viable, the imposition



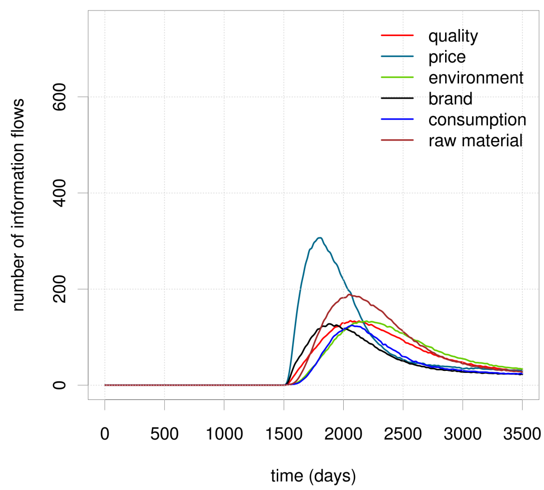
(a) Communication about unbranded conventional fuel



(b) Communication about branded conventional fuel



(c) Communication about premium fuel



(d) Communication about BtL-fuel

Figure 6.10.: Number of communication events by attributes over time for $p_{BtL} = 1.3$ (5 consumer assignments to nodes x 10 random seeds = 50 replications)

of this rule does not impact the diffusion process since the minimum market share requirement is passed at all gas stations. At higher price levels, however, there is a kink in sales growth as the product is discontinued at some points of sale where sales do not meet expectations. This impact is very moderate at a price of $p_{BtL} = 1.3$, but it is dramatic for a price of $p_{BtL} = 1.4$, which is above that of the "premium" fuel product.

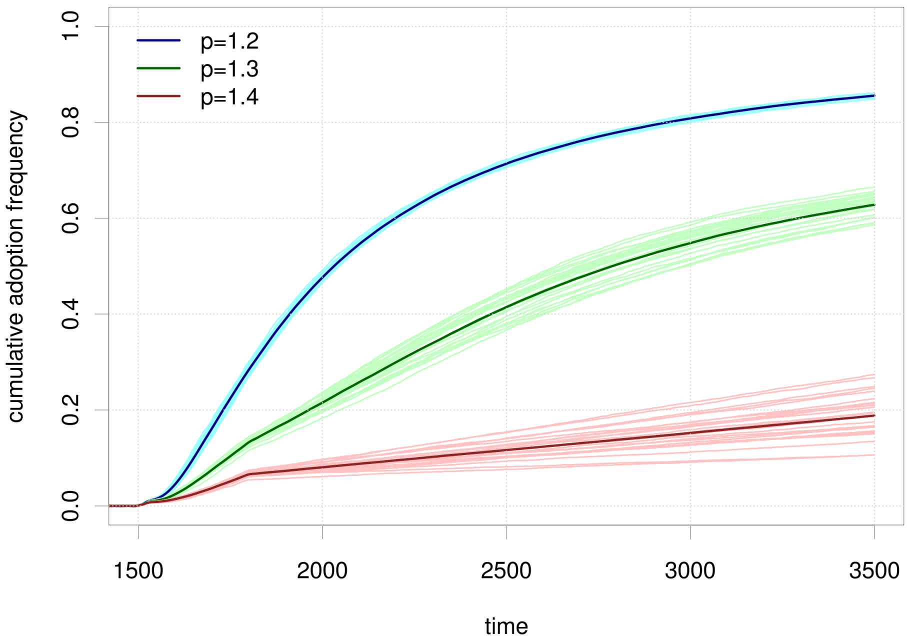


Figure 6.11.: BtL-fuel adoption for discontinuation scenario ($p_{BtL} = 1.2/1.3/1.4$) (5 consumer assignments to nodes x 10 random seeds = 50 replications)

With respect to communication behavior, there are no significant differences in communication behavior, as can be seen from the plots included in Subsection A.4.2.

6.7. Sensitivity analysis

In this section, we discuss results of a sensitivity analysis that we performed to evaluate the robustness of findings when different key parameters are varied. Table 6.6 summarizes the parameter ranges tested. The central case values used in our simulation scenarios in the previous section are printed in bold and parameters are manipulated individually on several levels as listed in the table.

6.7.1. Population size

An important decision that has to be made when conducting agent-based simulations is the number of agents to use. Since it is not feasible to simulate the entire Austrian fuel consumer

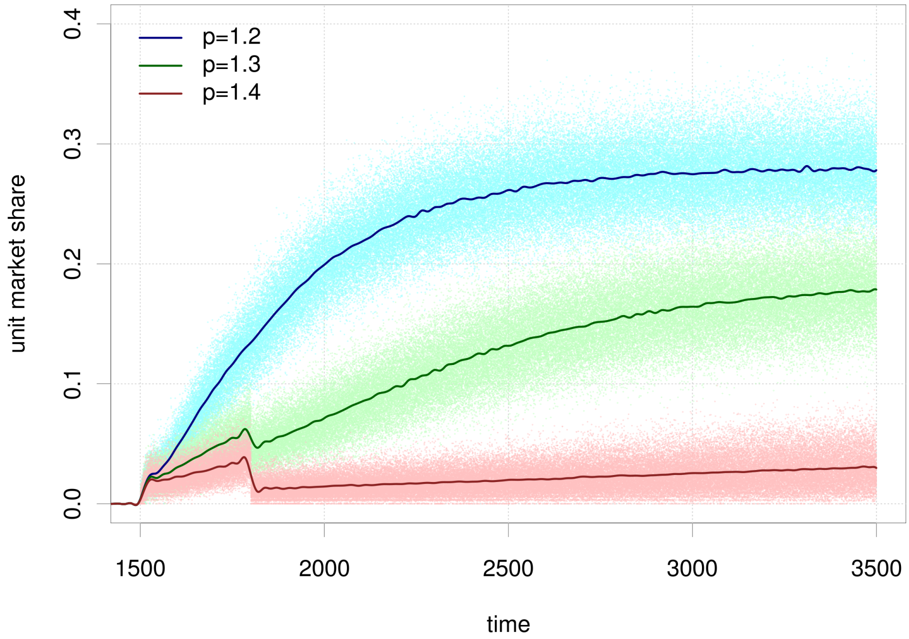


Figure 6.12.: BtL-fuel unit market share curves for discontinuation scenario ($p_{BtL} = 1.2/1.3/1.4$) (5 consumer assignments to nodes x 10 random seeds = 50 replications)

Parameter	values (central case value in bold)
Number of agents	1,000; 5,000; **10,000**; 15,000
Social network parameters	$\alpha = -1, \beta = 1$ $\alpha = -2, \beta = 1$ $\alpha = -3, \beta = 1$ $\alpha = -4, \beta = 1$ $\alpha = \mathbf{-5}, \beta = \mathbf{1}$ $\alpha = -1, \beta = 2$ $\alpha = -1, \beta = 3$
Average number of edges per node	4; **6**; 8; 10

Table 6.6.: Sensitivity analysis parameter ranges

population and only limited empirical data is available, we decided to use a population of $n^{consumers} = 10,000$ consumer agents in our experiments. To analyze whether results are robust when a different population size is used, we performed simulation experiments with a population of $n^{consumers} = 1{,}000; 5{,}000; 15{,}000$ consumers and found that results are very robust.

As expected, the variance in the results reduces as the number of agents increases, but the paths of BtL-fuel market shares over time are virtually identical for all population sizes. This can be clearly seen from Figure 6.13a, which plots the average unit market share development for all population sizes tested and indicates the results of individual replications by points. For $n^{agents} = 1,000$, the range of sales curves obtained is still very large and it may take a long time before the first agents decide to adopt. On average, it takes longer before a sufficient number of agents are informed for the innovation to "take off" and final market shares at the end of the simulation are therefore lower for $n^{agents} = 1,000$ than for larger populations, as illustrated in Figure 6.13c. However, for a population of $n^{agents} = 5,000$, results are already very consistent with those obtained with a higher number of agents.

Overall, we find that the chosen population size of $n^{agents} = 10,000$ yields robust results with respect to the number of agents in used in the simulation.

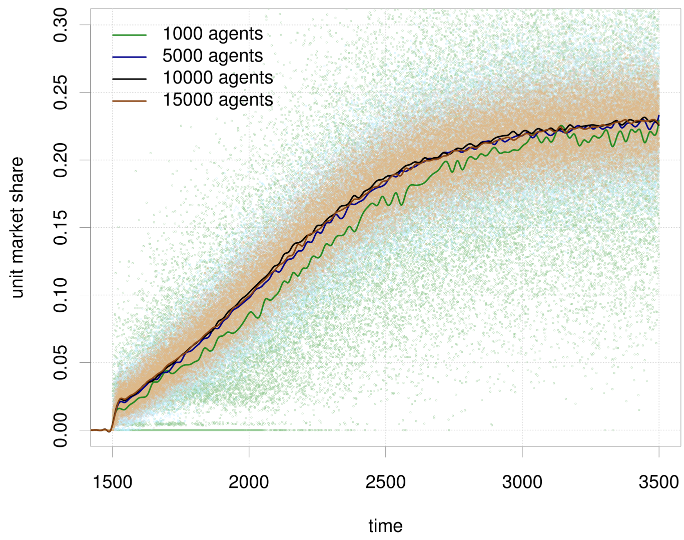
6.7.2. Social network parameters

Social network parameters define the channels through which information about products and their characteristics spreads and thereby determine the structure of interactions. Hence, these parameters are hypothesized to impact the speed of diffusion. In our sensitivity analysis with respect to social network parameters, we investigate the influence of the network density parameter $n_{link}^{spatial}$, the spatial parameter α, and the clustering parameter β.

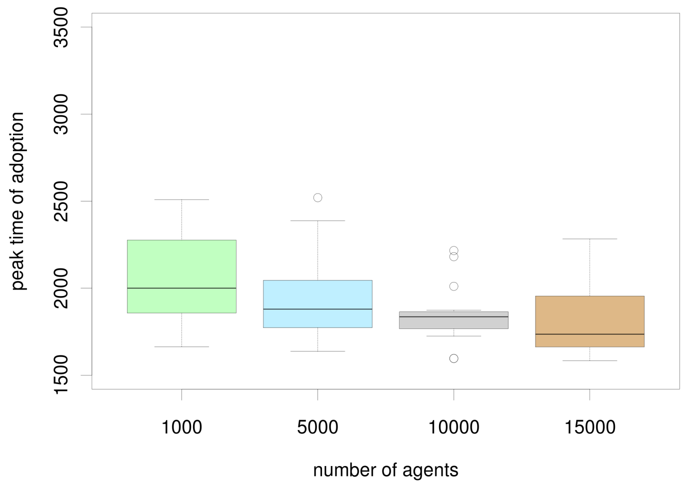
6.7.2.1. Number of edges

Network density, which is determined by the number of edges $n_{link}^{spatial}$ created per vertex, is expected to have a large impact on adoption and market share development, because information spreads faster in more densely structured networks. Note that the average number of nodes per agent is $2 \times n_{link}^{spatial}$, since only bidirectional links (i.e., no self-loops) are used. Hence, the tested parameters $n_{link}^{spatial}$ correspond to an average number of 4/6/8/10 communication links per consumer agent, respectively.

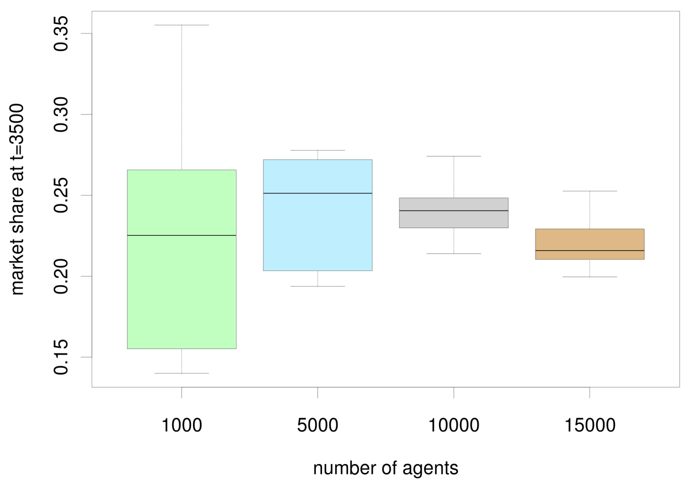
Figure 6.14a indicates that results are consistent with the expected effect by showing that a higher value of $n_{link}^{spatial}$ tends to be associated with faster sales growth. Figure 6.14b also shows that a higher number of links is consistently associated with an earlier peak time of adoption (i.e., the time in each simulation run at which the number of new adopters was greatest, which corresponds to the steepest point on the adoption curve). Differences in final market shares at



(a) BtL-fuel unit market share development (averages)



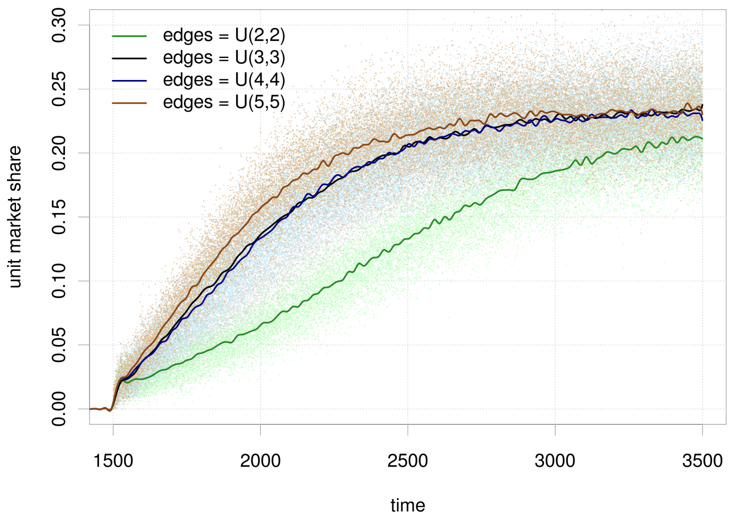
(b) Distribution of peak times of adoption times



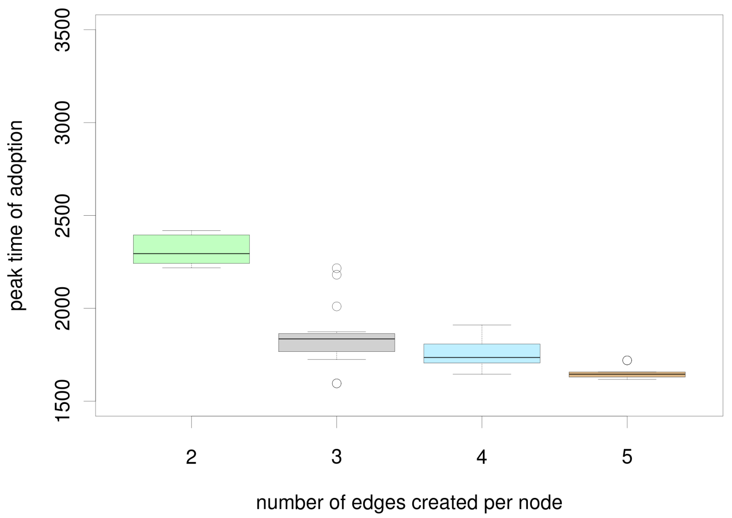
(c) Distribution of final market shares at $t = 3500$

Figure 6.13.: Sensitivity analysis w.r.t. number of consumers; $n^{consumers} = 1000/5000/10000/15000$; 15 realizations per parameter setting

$t = 3,500$ are insignificant, with the exception of $n_{link}^{spatial} = 2$, for which the system converges to a steady state after the simulation horizon, and the market share remains below the share achieved in more densely structured networks. The large difference in the path of sales growth, which is very similar for $n_{link}^{spatial} = 3/4/5$, can be explained by the fact that the network becomes very loosely structured and is not fully connected (contains small, isolated sub-graphs).



(a) BtL-fuel unit market share development (averages)



(b) BtL-fuel peak times of adoption

Figure 6.14.: Sensitivity analysis w.r.t. number of edges; $n_{link}^{spatial} = 2/3/4/5$; 15 realizations per parameter setting

6.7.2.2. Spatial parameter

Figure 6.15a plots the average unit market share curves for BtL-fuel for various values of the social network parameters α and β. A comparison of the the diffusion curves for $\alpha = -1/-$

$2/-3/-5; \beta = 1$ reveals that a lower value of α, and thus a more local interaction structure (due to a higher "penalty" for distance in the construction of the network), tends to lead to slower growth in sales. In more globally structured networks, by contrast, information about an innovation can spread more easily across longer distances and is less likely to "get stuck" in a remote local part of the social network. This interesting result is confirmed by a theoretical experiment on the impact of network structure, which is included in Section A.5.

Figure 6.15b also suggests that diffusion peaks earlier in more globally structured networks because information will, on average, take longer to reach the whole population if individuals exchange information only with peers in their immediate local environment.

For our application case, we can conclude that the estimated market share curve is a rather conservative estimate with respect to social network parameters, since relatively low values for both α and β were chosen and both higher values of α and higher values of β are associated with faster diffusion and sales growth.

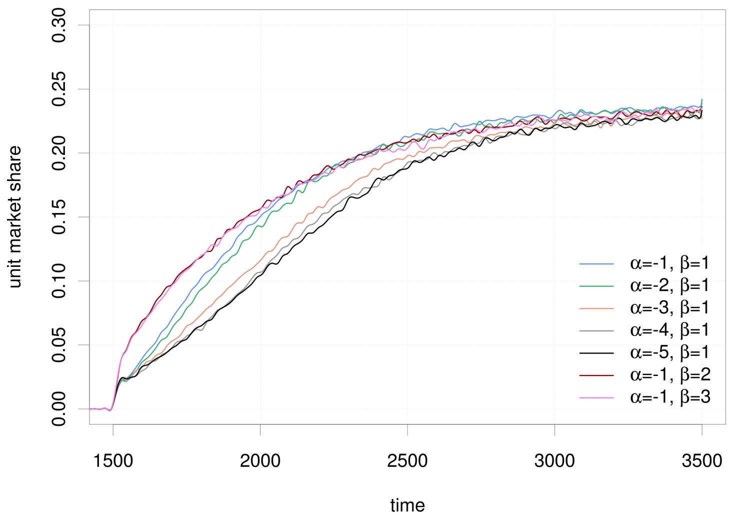
6.7.2.3. Clustering parameter

Results presented in Figure 6.15 suggests that the clustering parameter β positively impacts sales growth and that higher amounts of clustering tend to be associated with earlier peak times of adoption. This result is consistent with existing findings in the literature (cf. Subsection 3.4.2) as well as results of theoretical experiments on the impact of network structure conducted with the simulation, which are included in Section A.5.

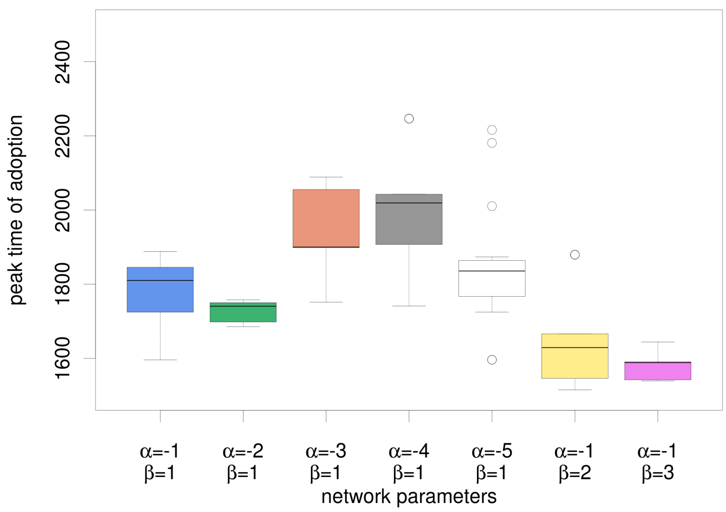
Overall, we find that the parameters α and β affect the speed of sales growth and the peak time of adoption considerably. However, the simulation results for our specific application case also suggest that the effect of network structure is not as pronounced as might be expected because sales growth is not only limited by the spread of information, but also because it takes times for agents to adapt their purchasing behavior by switching to gas stations that carry the new product and to accumulate experience in using the product.

6.8. Validation

Validating agent-based models is a challenging task due to their high degrees of freedom and a number of methodological issues (cf. Fagiolo et al., 2007; Ormerod and Rosewell, 2009). Whereas more traditional modeling techniques can rely on a standard set of established tools and criteria for validation, *"there is no consensus at all about how (and if) agent-based models should be empirically validated"* (Fagiolo et al., 2007). In a diffusion of innovations context, agent-based models share many of the problems of aggregate models with respect to validation, but these problems are exacerbated by the difficulty of simultaneously mapping networks, collecting individual-level data, and tracking diffusion (Peres et al., 2010). Nevertheless, ensuring a satis-



(a) BtL-fuel unit market share development (averages)



(b) Distribution of peak times of adoption for multiple social network parameter settings

Figure 6.15.: Sensitivity analysis w.r.t. social network parameters α and β; 15 realizations per parameter setting

factory range of accuracy matching the simulated model to the real world is clearly important (Fagiolo et al., 2005), especially when models are used not merely as tools for abstract theoretical inquiry, but to inform and support important real-world decisions.

To select appropriate steps for a careful validation of the proposed model in the context of the application presented in this chapter, we mainly followed Knepell and Arangno (1993), Carley (1996), Garcia et al. (2007), and (Ormerod and Rosewell, 2009). In particular, we structure our validation efforts into the following broad categories (cf. Knepell and Arangno, 1993)[6]:

1. Conceptual validity
2. Internal validity
3. Micro-level external validity and
4. Macro-level external validity
5. Cross-model validation

Conceptual validity is reached when the underlying conceptual model is adequately characterizing the real-world phenomenon under study; internal validity refers to whether the computer code works as intended; external validity is concerned with the linkage between the simulated and the real. Finally, cross-model validation compares the results of different models to judge the degree to which they match.

6.8.1. Conceptual validity

In order to ensure conceptual validity of the model, we relied on the well-established conceptual framework of the diffusion of innovations by Rogers (2003). Furthermore, we grounded the design of model mechanisms in the theoretical literature wherever possible.

6.8.2. Internal validity

To ensure internal validity, the software was tested thoroughly during the implementation process to ensure that it is correct with respect to its conceptualization. To this end, we relied extensively on unit and integration testing. The former is a method for individually and independently testing small units of code, such as methods, to ensure that their implementation is correct. The latter is an approach for testing groups of code to ensure that the individually tested units work as intended when combined. Unit testing was mainly applied to "critical" agent methods and model parameterization code. Integration tests were performed to ensure that the simulation always produces the same results for the same parameter setting and random seed, as well as to test "extreme" parameter settings and ensure that results obtained are plausible. For instance, we set the price of the BtL-fuel to an extremely high level (€ 5/liter) relative to available alternatives and verified that the product fails to diffuse. Another example is a

[6] Terminology in the validation literature is somewhat inconsistent. The current systematization was chosen because it was deemed appropriate for the purpose of validating the model.

test that ensures that no diffusion takes place when no social network exists (i.e., no links are created; in that case, only a small fraction of consumers that are persuaded by advertising at the point of sale can adopt). Various similar "sanity check" scenarios were tested to further increase confidence in the internal validity of the model.

6.8.3. External micro-level validity

Once the conceptual and internal validity of the model had been established, we proceeded to validate the model externally on the micro-level by examining whether the micro-level mechanisms in the model as well as the characteristics and initial conditions of the agents are valid. The terms validation, verification, and calibration are not used consistently in the literature; we follow (Garcia et al., 2007, p. 250) and distinguish between calibration, defined as validation of the model's inputs, and verification, defined as the validation of the model's output (Garcia et al., 2007, p. 250).

Calibration As a first step towards establishing micro-level validity, we examined *parameter validity* (Carley, 1996), which Garcia et al. define as examining *"if the characteristics and initial conditions assigned to an agent appear realistic"* (Garcia et al., 2007, p. 849).

To this end, we carefully examined the survey data used for parameterization and corrected missing and implausible values wherever necessary. In particular, we completed 77 missing values for the survey question that asked for the kilometers traveled per year with the average value for passenger vehicles obtained from Environment Agency Austria. We also checked the conjoint data for inconsistent preferences, but did not find any systematic problems.

Further micro-level mechanisms that could be used to calibrate the model, if detailed micro-level data was available, are provided in the model. The attraction parameter that affects the probability that a given point of sale is chosen for a gas stop, for example, could be used to account for differences in sales volumes at individual gas stations.

Verification To verify the model's outputs on the micro-level, we closely examined logfiles and traced individual agents' history across a simulation run to assess whether the observed behavior appears realistic. In particular, our micro-level verification efforts revolved around (i) the selection of points of sale, (ii) communication behavior, and (iii) purchase decisions. Point of sale selection behavior in the simulation was consistent with reported behavior from survey data. Detailed data for the empirical validation of communication behavior was not available, but agents' behavior was found to be realistic with respect to our assumptions. Finally, we verified the purchase choice model by comparing the decisions made by our agents to the decisions made by respondents in the conjoint analysis. In particular, we tested whether agents, when offered the same alternatives like the respective respondent in the conjoint analysis that was used to parameterize the agent, choose the same option. The choices made by the agents matched the real person's revealed preference in most cases, which suggests that the chosen preference model can adequately capture consumers' preferences. More precisely, we found that the use of piecewise linear, additive preferences in our model resulted in approximately 90% consistent choices (8,939 of the 10,000 individual decisions in the conjoint experiment).

Because we suspected that lexical preferences were also a potential alternative model for representing consumers' preferences in this particular application case, we closely inspected the revealed preference data (i.e., the choices made by respondents in the conjoint experiment). According to this alternative assumption, consumers would choose the alternative that scores best in the most important attribute (typically price), and only consider alternatives that score as good as the best alternative in the most important attribute. However, the conjoint data did not support this alternative assumption since the number of correct choices when always choosing based on the attribute that contributed the highest partworth or choosing only based on price lead to a lower number of correct choices (approximately 73%). Hence, we concluded that a compensatory choice model that presumes piecewise linear, additive preferences can adequately capture consumers' preferences.

6.8.4. External macro-level validity

Macro-level validation of diffusion models is difficult. If an actual realization of the diffusion process had already happened, the diffusion model would not be needed. A limited number of approaches to overcome this inherent problem are available and we discuss the approaches that we used in this section.

Calibration No calibration of input parameters based on macro-level empirical data was performed due to the lack of adequate data. However, such calibration could in principle be performed using aggregate time-series data on the diffusion and sales growth of premium fuels. However, such data was not obtainable for the present research because fuel sales data is a closely kept commercial secret. A decision-maker that has such historic data available, however, could calibrate the model before using it for the simulation of biofuel adoption.

Verification We first established face validity on the macro-level by monitoring the diffusion rate and the development of market shares and securing the opinion of an energy market expert, who asserted that the output looks valid. The model reproduces stylized facts such as the typically S-shaped curve of innovation diffusion. Market shares in steady state are consistent with the market shares that can be expected from the conjoint data.

As noted in the previous section, data on the adoption of premium fuels, which could also be used for macro-level verification purposes, was not available. The distribution of market shares between branded and unbranded operators, which could also help in verifying model output on the macro-level, is also not publicly available. However, we could at least compare premium market shares in the simulation against the scarce publicly available information. In our simulation experiments, premium fuels reached a market share of approximately 15% in the steady state prior to the introduction of the BtL-fuel. According to newspaper reports, "Shell V-Power" reached a market share of approximately 6–7% shortly after its market introduction in Germany and a 15% market share was projected for "V-Power Diesel" (Bekert, 2003; Müller, 2004). Obviously, this data is insufficient for detailed calibration and verification purposes, but it suggests that our simulation results are plausible.

Overall, we can conclude that *process validity* (Carley, 1996), which *"ascertains whether the overall model simulation makes sense on a macro-level"* (Garcia et al., 2007, p. 849), is supported.

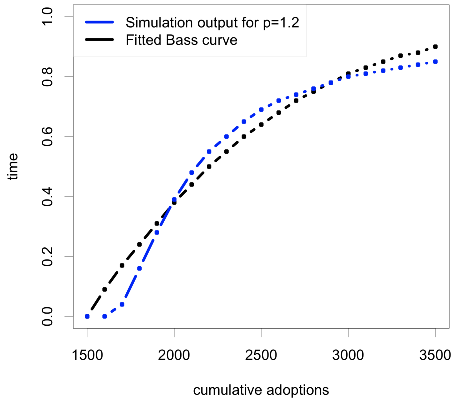
6.8.5. Cross-model validation

An alternative approach to validate a simulation model is to compare its output to that of some other model. This idea was developed in the literature under labels like "cross-model validation" (Knepell and Arangno, 1993), "aligning" (Axtell et al., 1996), and "docking" (Olaru et al., 2009). We adopt the first term and use the Bass model as an aggregate-level meta-model to compare the simulation results against because it provides an empirical generalization and is currently the most widely accepted aggregate-level model. If we can show that the simulation output is reasonably similar to output produced by the Bass model, then this serves as an indication that the simulation replicates stylized facts formalized in the Bass model.

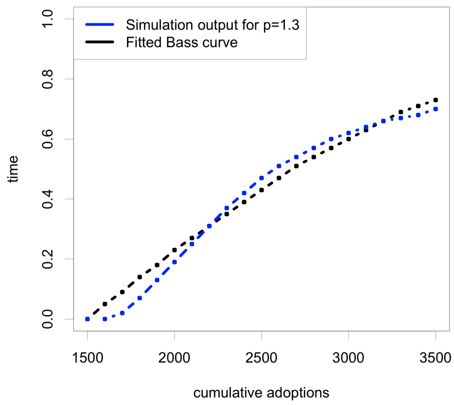
In order to cross-validate the model, we used the average diffusion curves of our base scenario[7] and fitted the Bass model to these respective curves for three price levels via nonlinear least squares (Srinivasan and Mason, 1986). A comparison of the simulation output to the Bass model curve that best fits the data generated by the simulation is presented in Figure 6.16. Whereas the average diffusion curve obtained from the simulation cannot be perfectly reproduced by the Bass model and the estimated coefficients are relatively low due to the long diffusion time, the plots indicate that the simulation does produce a similar characteristic S-curve. Overall, we find that the Bass model can be fitted to the simulation output reasonably well ($R^2_{p=1.2} = 0.68; R^2_{p=1.3} = 0.68; R^2_{p=1.4} = 0.61$) and hence conclude that the simulation does indeed reproduce the stylized facts embodied in the Bass model. This cross-model validation further supports confidence in the results. While we found that similar, although not identical results could be produced the Bass model as well, the major advantage of the agent-based model is that results are produced by a causal model based on empirical data that can be collected before the market introduction of the innovation whereas parameter of the Bass model can only be estimated after the fact or

[7] Discretized in intervals of $\Delta t = 100$.

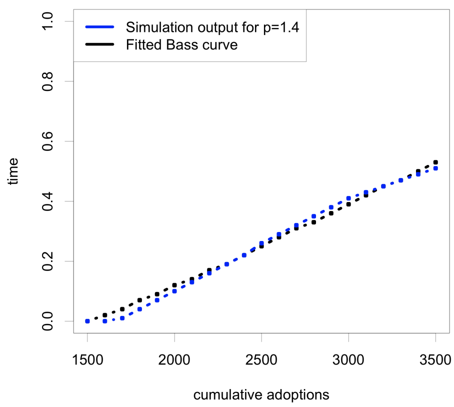
by analogy with historic data on the diffusion of similar products.



(a) Average adoption curve produced by the simulation and fitted Bass curve ($p = 0.087$, $q = 0.045$, $m = 1$) for $p_{BtL} = 1.2$



(b) Average adoption curve produced by the simulation and fitted Bass curve ($p = 0.046$, $q = 0.05$, $m = 1$) for $p_{BtL} = 1.3$



(c) Average adoption curve produced by the simulation and fitted Bass curve ($p = 0.02$, $q = 0.06$, $m = 1$) for $p_{BtL} = 1.4$

Figure 6.16.: Cross-model validation of the agent-based model and the Bass model

7. Conclusions

This chapter concludes the thesis by summarizing the main research contributions, discussing managerial implications, and providing directions for future work.

7.1. Summary of main research contributions

As outlined in Chapter 1, the overall aim of the research presented in this thesis was to contribute towards bridging the gap between highly stylized theoretic models of innovation diffusion on the one hand, and specialized models for particular innovations on the other hand. This area is challenging and at the same time also highly promising both from a scientific and a managerial perspective. The overall aim was operationalized by formulating various specific objectives. In the following, we highlight in detail the extent to which these objectives have been met.

Objectives 1 and 2: Thoroughly review the available literature and identify advantages and limitations of an agent-based diffusion modeling approach

Objectives one and two were accomplished by providing a general introduction to the literature on innovation diffusion, outlining various approaches for modeling this phenomenon, and critically reviewing the available agent-based models published in the literature to date.

Traditional aggregate models of innovation diffusion were discussed and their strengths and limitations were highlighted. In particular, it was shown that these models are limited (i) in their explanatory and predictive power, (ii) in their potential to consider consumers' heterogeneity, and (iii) in their ability to adequately account for the structure of social interactions. Furthermore, since aggregate models are typically focused on explaining past behavior, it was concluded that they offer only limited prescriptive guidance to decision-makers, some extensions that incorporate decision variables into these models notwithstanding.

Following that, the literature on system dynamics models as an alternative aggregate-level approach was reviewed. We found that these models provide valuable insights because they can account for a rich set of dynamic feedback structures, but concluded that they offer limited potential to account for heterogeneity and social structure.

Turning to disaggregate approaches, we first discussed micro-economic and stochastic brand choice models. We found that micro-level models offer valuable insights and inspiration for diffusion modelers, but usually cannot be applied directly for the modeling and forecasting of diffusion processes because they focus exclusively on the micro-level and typically do not provide explicit functions for aggregate diffusion. Our review of dynamic brand choice models showed that these models are useful in situations where innovations fit into existing product categories and replacement largely determines the total market size. For modeling the diffusion of innovations, which consumers are usually not already familiar with, however, they are less suitable because they lack elementary diffusion mechanisms such as word of mouth communication.

Finally, we identified agent-based modeling, a methodology that has increasingly been adopted in the social sciences in recent years, as an alternative that potentially allows researchers to overcome the limitations of other diffusion modeling techniques. Agent-based modeling captures emergent phenomena in complex systems on the macro-level by simulating the behavior and interactions of entities on the micro-level. We found that this methodology offers a number of benefits in the context of innovation diffusion research, including its ability to capture the complex structure and dynamics of diffusion processes, explicitly model micro-level drivers of innovation adoption, and account for consumers' heterogeneity and the social structure of interactions.

Chapter 3 extended the literature review by critically discussing agent-based diffusion modeling techniques and agent-based models that have been published in the peer-reviewed literature to date. To inform the later model development, the chapter first analyzed how two critical elements in agent-based diffusion models — consumer adoption behavior and social influence — can be conceptualized. Following this, we discussed theoretical findings that were made possible through agent-based modeling techniques and reviewed the growing body of literature on specific applications and policy analyses.

The literature review identified a number of research gaps. In particular, we found that agent-based diffusion models have so far largely neglected geographic space, competition, repeat purchases, and the role of product characteristics in the diffusion of an innovation.

Objective 3: Design and implement an agent-based model that can support decision-makers in planning the market introduction of an innovation

Based on an extensive literature review, the model development process was initiated by formulating a number of key objectives in order to close the identified research gaps. These objectives were as follows: (i) develop of a versatile model, (ii) balance abstraction and descriptiveness, (iii) model space explicitly, (iv) model the innovation-decision process comprehensively, (v) account for competitive interaction, and (vi) incorporate multi-attribute consumer decision-making. Next, we outlined a modeling strategy that addresses key methodological issues that have typically not received sufficient attention in the prior literature. The chosen strategy comprises the continuous modeling of time in order to avoid imposing artificial structure upon the diffusion process, and the explicit, continuous modeling of space. We then proceeded to the design of the formal model which was specified by introducing and discussing its elements and mechanisms in detail. Innovative aspects of the resulting model, which distinguish it from existing approaches, include the following: (i) consumers and points of sale are embedded in geographic space, (ii) distance is accounted for in the generation of social network models, (iii) information exchange on specific topics (i.e., product attributes) is modeled explicitly, (iv) multiple products allow for the simulation of competitive diffusion, (v) repeat purchase decisions and consumers' post purchase evaluation are considered, (vi) product launch strategies can be evaluated with respect to all marketing mix variables (i.e., product design, distribution, communication, and pricing).

After fully specifying the formal model, we then provided an overview of available tools for building agent-based simulations, outlined the platform and tools chosen for the implementation of the model, and described the architecture of the software implementation of the proposed model. To this end, we also outlined software design objectives as well as the chosen means to accomplish these objectives.

Objective 4: Demonstrate the potential of the developed model by means of an empirically grounded application case study

Finally, objective four was achieved by means of a case study on the diffusion of a second generation biofuel on the Austrian market. This innovation was chosen both because it is particularly relevant from a societal perspective, and because it represents a good example for an innovation whose diffusion cannot be adequately captured by existing models. Whereas existing diffusion models in the literature are typically exclusively concerned with the diffusion of consumer durables and hence cover only part of the innovation-decision process, the model developed in this thesis, by contrast, does not neglect phases in the process that occur after the initial purchase. In particular, the proposed model accounts for consumers' post-purchase product evaluation, models information exchange on product characteristics based on consumers' first-hand experiences, and describes how initial adoptions and repeat purchases jointly shape the diffusion process. For the application case at hand, this is particularly important because decision-makers that consider an investment in the infrastructure necessary to launch a second generation biofuel are more interested in evaluating its total market potential than in the number of initial adopters over time.

After providing the background on biofuels, we discussed the array of data collection techniques and sources used to obtain the data required to instantiate the model for the particular application case. We thereby demonstrated that the need for detailed micro-level data, which may be considered a limitation of the agent-based approach, may be overcome and that the simulation can be grounded in empirical data. Finally, we introduced the experimental design, discussed the results of our experiments on biofuel diffusion, and conducted a sensitivity analysis.

We closed by discussing validation issues in detail.

7.2. Managerial implications

As to the second generation biofuel application, our findings for the Austrian market suggest that while a competitive price is unsurprisingly an important driver for adoption, there is clearly a market potential for the innovation even at a price level above that of conventional fuels. The simulation results also indicate that a considerable market share may be achieved within the next four years following the introduction of such a product. Both results should be of value for investors planning the market introduction of a second generation biofuel.

Decision-makers may use the model to simulate energy market scenarios and their impact on the competitiveness of alternative fuels. It was also demonstrated that the simulation enables a decision maker to test the effectiveness of various approaches towards selecting gas stations situated in a geographically opportune location for distribution, while accounting for limited production capacity, availability of rich sources of biomass, and the geographic concentration of consumers.

7.3. Limitations and avenues for future research

This thesis successfully developed a model that can simulate the diffusion of repeat purchase products in a competitive setting and, by means of an application case, demonstrated how this model can be instantiated with empricial data to support decision-makers in developing market introduction strategies for new products. Like in any research, however, there are a number of limitations. In this concluding section, we highlight major remaining challenges and propose potential directions for future research.

First, although we grounded all parts of the model in well-established theory wherever possible, various aspects could be refined if more detailed theoretical results should become available. One area where further theoretical improvements would be particularly useful is the modeling of social networks and WoM interactions. Recent advances in network modeling have allowed diffusion researchers to employ more realistic computer-generated social network models than the random networks that were typically used in early studies. In terms of generating networks that share characteristics of real-world social networks, the spatial algorithm adopted in the current thesis also yields promising results. However, it is still unclear which generative algorithms and parameter settings are most appropriate for the modeling of consumers' interactions. Because of the considerable impact of social structure on diffusion patterns, this is an important area for future empirical research. Such research should consider that different types of markets are associated with different types of networks and accordingly aim to identify appropriate network models and parameter settings for different market types and product categories. Such advances may contribute significantly towards establishing agent-based diffusion models as tools for managerial applications.

Furthermore, although we relied on available literature on WoM referral behavior to ground our communication model, there is currently no fully developed theoretical framework that explains *what* (contents of communication, i.e., products and product attributes) and *when* consumers exchange information on new products. This may be attributed to the considerable differences that exist between product categories and markets, which make generalization challenging. The proposed model can be parameterized, extended, and modified in various ways to account for differences in communication behavior for various types of products. However, in order to do so, more empirical research and theory development are necessary.

The model could also be extended to allow for its use in a wider range of applications. To this end, additional aspects and alternative mechanisms need to be incorporated. The assumption of periodic consumption patterns, for example, fits the biofuel application well, but it is only appropriate for a limited range of consumer items. For other types of products, alternative mechanisms for triggering needs have to be incorporated. For certain products, it may also be necessary to explicitly model rejection of an innovation.

In the biofuel application case, we used various data sources and an array of collection techniques to obtain detailed data for model parameterization. Nevertheless, we had to rely on assumptions or stylized facts in the design of some model elements. In particular, we had to make specific assumptions on the probability of WoM communication about specific aspects of a fuel product as a function of perceived changes in utility. We also had to make informed assumptions about the characteristics of the novel product and the market conditions (i.e., available alternative products and their characteristics and price levels) during launch. Before using the model to develop a strategy for the actual launch of a second generation biofuel, these aspects should be investigated in more detail. Furthermore, further validation using detailed data on premium fuel adoption and sales would also be highly beneficial and further improve confidence in the model's ability to provide valid forecasts in this setting.

A thoroughly validated model could then be used to evaluate adaptive pricing policies that take competitors' behavior into account. In the future, the model may also be used to decide when to advertise, where to advertise, and which product characteristics to emphasize in individual stages of the diffusion process.

Finally, while the model introduced in this thesis is primarily targeted at decision-makers planning the market introduction of a new product, it may also be useful for other stakeholders and purposes. The simulation may, for example, also be highly useful as a tool for learning. Scenarios that enable students to test various strategic choices can be designed easily. In the future, the model could also be expanded into an interactive business gaming simulation in which multiple participants compete in a simulated market, each controlling their own firm and launching their own products.

Simulation results for the biofuel application may also be of considerable interest to policy makers, who face the pressing need to design policies that reduce CO_2 emissions in order to mitigate climate change. The simulation could be used to investigate strategies to spur the diffusion of environmentally benign alternatives to petroleum-based fuels through taxation and subsidization.

Despite the remaining challenges and limitations, this thesis demonstrated agent-based models' potential to support managerial decisions in the context of planning the market introduction of an innovation. The field offers excellent opportunities for further research in the future.

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A. Appendix

A.1. Complete list of model parameters

Parameter	Explanation	value	source
C	Set of consumer agents	$n^{consumers} = 10,000$ consumer agents created from survey data of 1,000 respondents	online survey
A	Set of attributes	A_1: quality A_2: price A_3: environment A_4: brand A_5: consumption A_6: raw material	expert interview, focus-group, pre-study
S	Set of points of sale	$\{S_1, \ldots, S_{757}\}$ discount gas stations $\{S_{758}, \ldots, S_{1571}\}$ branded gas stations	`http://openstreetmap.org`
L_l^{pos}	Point of sale location	each gas station assigned to actual geographical location	`http://openstreetmap.org`
$s_{i,l,t}$	Availability at point of sale S_l	$s_{1,l,t} = 1 \quad \forall l = 1, \ldots, 757; t \geq 0$ $s_{2,l,t} = 1 \quad \forall l = 758, \ldots, 1571; t \geq 0$ $s_{4,l,t} = 1$ for $t \geq 750$, 548 gas stations $s_{4,l,t} = 1$ for $t \geq 1500$, 189 gas stations $s_{i,l,t} = 0$ otherwise	actual availability/ assumed scenario
k_l	point of sale attraction parameter	$k_l = 1 \quad \forall l = 1, \ldots, 1571$	scenario assumption
o_j	Attribute “observability”	$o_1 = 0.2$ $o_2 = 1$ $o_3 = 0.1$ $o_4 = 0.6$ $o_5 = 0.6$ $o_6 = 0.1$	assumption
P	Set of products	P_1: conventional fuel unbranded P_2: conventional fuel branded P_3: “premium” fuel (branded) P_4: BtL fuel	assumed scenario

Parameter	Explanation	value	source
$v_{i,j}^{true}$	True product attribute values	$v_{1,1}^{true} = 0$ $v_{1,2}^{true} = 1.2$ $v_{1,3}^{true} = 0$ $v_{1,4}^{true} = 0$ $v_{1,5}^{true} = 1$ $v_{1,6}^{true} = 0$ $v_{2,1}^{true} = 0$ $v_{2,2}^{true} = 1.22$ $v_{2,3}^{true} = 0$ $v_{2,4}^{true} = 1$ $v_{2,5}^{true} = 1$ $v_{2,6}^{true} = 0$ $v_{3,1}^{true} = 1$ $v_{3,2}^{true} = 1.35$ $v_{3,3}^{true} = 0$ $v_{3,4}^{true} = 1$ $v_{3,5}^{true} = 1$ $v_{3,6}^{true} = 0$ $v_{4,1}^{true} = 1$ $v_{4,2}^{true} = 1.3$ $v_{4,3}^{true} = 1$ $v_{4,4}^{true} = 1$ $v_{4,5}^{true} = 0.95$ $v_{4,6}^{true} = 1$	assumed scenario
$G_k(t)$	Interpurchase time distribution fun.	$Pois(\lambda)$, λ determined individually for each agent from reported driving behavior	online survey
$a_{i,k}^{prod}$	Product awareness	at the beginning of the simulation set to $a_{1,k}^{prod} = 0 \quad \forall k \in C$ $a_{2,k}^{prod} = 0 \quad \forall k \in C$ $a_{3,k}^{prod} = 1 \quad \forall k \in C$ $a_{4,k}^{prod} = 1 \quad \forall k \in C$	assumed scenario
$a_{j,k}^{attr}$	Attribute awareness	at the beginning of the simulation, set to $a_{1,k}^{attr} = 0 \quad \forall k \in C$ $a_{1,k}^{attr} = 1 \quad \forall k \in C$ $a_{1,k}^{attr} = 0 \quad \forall k \in C$ $a_{1,k}^{attr} = 1 \quad \forall k \in C$ $a_{1,k}^{attr} = 0 \quad \forall k \in C$ $a_{1,k}^{attr} = 0 \quad \forall k \in C$	online survey
$u_{j,k}()$	Utility functions for each agent C_k and attribute A_j	piecewise linear functions parameterized individually from conjoint data for each agent	conjoint experiment
$Lcons_k$	location of consumer agent C_k	assigned according to population density data	census (2001) data

Parameter	Explanation	value	source
$n_k^{posHist}$	number of recently visited points of sale considered in point of sale selection process	$n_k^{posHist} = 1$ for 2690 agents $n_k^{posHist} = 4$ for 6120 agents $n_k^{posHist} = 0$ for 1190 agents	survey data
$p_k^{recentPOS}$	probability of choosing a recently visited point of sale in point of sale selection process	$p_k^{recentPOS} = 1$ for 2690 agents $p_k^{recentPOS} = 0.8$ for 6120 agents $p_k^{recentPOS} = 0$ for 1190 agents	survey data
$\alpha_k^{posSelect}$	spatial exponent that weights distance in random point of sale selection	$\alpha_k^{posSelect} = -5$	assumption
ε^{pos}	point of sale selection error	$\varepsilon^{pos} \sim U(0,0)$ (always pick best)	assumption
$m_{init}^{spatial}$	fully connected "seed vertices"	$m_{init}^{spatial} = 4$	
$n_{link}^{spatial}$	number of edges to create for each node	$n_{link}^{spatial} = 3$ (i.e., 6 edges per node on av.)	survey data
$\alpha^{spatial}$	spatial exponent	$\alpha^{spatial} = -5$	assumption based on general sociometric studies
$\beta^{spatial}$	clustering exponent	$\beta^{spatial} = 1$	assumption based on general sociometric studies
$Y_{a,b}$	Communication interarrival time distribution function	$Pois(30) \quad \forall a, b$	assumption based on survey data
$w_{a,b}$	weighting of WoM influence	$w_{a,b} = 0.5 \quad \forall a, b$	assumption based on survey data
λ	exponential information decay	$\lambda = 0.2$	assumption
n^{bins}	number of bins in histograms that store attribute information	$n^{bins} = 10$	model parameter
w^{ad}	advertising influence weight	$w^{ad} = 0.2$	assumption
$P^{comm}(u)$	Function that assigns a selection probability to a given change in attribute utility valuation	piecewise linear function with interpolation points $\{(-10, 1); (-0.05, 1); (0, 0.01); (0.05, 0.15); (10, 1)\}$	assumption

Table A.1.: Complete list of model parameters

A.2. XML parameterization files for base scenario

Model Configuration

```
<ModelConfiguration>
  <agentInitialization>PROTOTYPE_BASED</agentInitialization>
  <productEvaluationModel>org.univie.quasimodi.core.model.utility.productEvaluation.UnsharpStrictProductEvaluationModel</productEvaluationModel>
  <communicationModel>org.univie.quasimodi.core.model.communication.DefaultC2CCommunicationModel</communicationModel>
  <communicationScheduling>ALTPERIODIC</communicationScheduling>
  <communicationProbabilityForUtilityChangeFunction class=”map”>
        <entry>
          <double>-10</double>
          <double>1</double>
        </entry>
        <entry>
          <double>-0.05</double>
          <double>1</double>
        </entry>
        <entry>
          <double>0.0</double>
          <double>0.01</double>
        </entry>
        <entry>
          <double>0.05</double>
          <double>0.15</double>
        </entry>
        <entry>
          <double>10</double>
          <double>1</double>
        </entry>
  </communicationProbabilityForUtilityChangeFunction>
</ModelConfiguration>
```

Listing A.1: `modelConf.xml`

Batch file

```
<SimulationBatch>
  <baseSimulationRunFile>run.xml</baseSimulationRunFile>
  <!-- Good random seeds from cern.jet.random.engine.RandomSeedTable -->
  <seeds class="list">
    <int>1299961164</int>
    <int>253987020</int>
    <int>669708517</int>
    <int>2079157264</int>
    <int>190904760</int>
  </seeds>
</SimulationBatch>
```

Listing A.2: `batch.xml`

Simulation run file

```
<SimulationRun>
  <modelConfigurationFileName>modelConf.xml</modelConfigurationFileName>
  <scenarioFileName>scenario.xml</scenarioFileName>
  <socialNetworkDefinitionFileName>socialNetworkParameters.xml</socialNetworkDefinitionFileName>
  <communicationPolicyFileName>seed_prod3_100_agents_at_500_prod4_100_agents_at_1000.xml</communicationPolicyFileName>
  <rolloutPolicyFileName>rolloutPolicy.xml</rolloutPolicyFileName>
  <pricingPolicyFileName>pricingPolicy.xml</pricingPolicyFileName>
  <chartOutputConfigurationFileName>chartOutputConfig.xml</chartOutputConfigurationFileName>
  <posProductPolicyFileName>productPolicy.xml</posProductPolicyFileName>
  <timeLimit>3500</timeLimit>
  <checkpointFinalState>false</checkpointFinalState>
  <simulationFileLogLevel>INFO</simulationFileLogLevel>
  <simulationConsoleLogLevel>INFO</simulationConsoleLogLevel>
  <writeHeadersInResultFiles>true</writeHeadersInResultFiles>
</SimulationRun>
```

Listing A.3: `run.xml`

Social network parameters

```
<SocialNetworkParameters>
<!--
  <socNetParam class="GeodesicClustering">
    <noEdgesDistribution class="UniformDistributionParameter">
        <min>3.0</min>
        <max>3.0</max>
    </noEdgesDistribution>
    <clusteringExponent>1</clusteringExponent>
    <geodesicExponent>-5</geodesicExponent>
  </socNetParam>
  <seed>1299961164</seed>
-->

  <assignConsumerAgentsFromNetworkFile>false</assignConsumerAgentsFromNetworkFile>
  <consumerLocationAssignerClass>org.univie.quasimodi.core.model.geo.PopulationDensityBasedLocationAssigner</consumerLocationAssignerClass>
  <consumerAssignmentShuffleSeed>190904760</consumerAssignmentShuffleSeed>

  <readNetworkFromFile>true</readNetworkFromFile>
  <writeNetworkToFile>false</writeNetworkToFile>
  <fileName>newGeodesicClustering_10000_seed=1299961164_edges=3_clustering=1_geodesic=-5.xml</fileName>
</SocialNetworkParameters>
```

Listing A.4: `socialNetworkParameters.xml`

Social network

```xml
<graphml xmlns="http://graphml.graphdrawing.org/xmlns/graphml"
      xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
      xsi:schemaLocation="http://graphml.graphdrawing.org/xmlns/graphml">
<graph edgedefault="directed" >
<node id="4662081" name="4662081" y="48.11263101857717" x="15.123489645394145" />
<node id="4662083" name="4662083" y="47.869367167470756" x="13.117508825721593" />
<node id="4662086" name="4662086" y="48.02512326953815" x="16.769965144676068" />
...
<node id="94683039" name="94683039" y="48.21810663023081" x="15.278493565504986" />
<edge source="34672731" target="44671243" name="0" credB="0.3" credA="0.3" />
<edge source="64677252" target="34672731" name="1" credB="0.3" credA="0.3" />
...
<edge source="94662343" target="14665295" name="29992" credB="0.3" credA="0.3" />
<edge source="94662343" target="54662190" name="29993" credB="0.3" credA="0.3" />
</graph>
</graphml>
```

Listing A.5: `geodesicClustering_10000_seed=1299961164_edges=3_clustering=1_geodesic=-5.xml`

Scenario

```xml
<ScenarioWithIndividualAgentData>
  <name>Base Scenario</name>
  <notes>
  </notes>
  <attributes>
    <Attribute>
      <id>0</id>
      <name>Quality</name>
      <observability>0.2</observability>
    </Attribute>
    <Attribute>
      <id>1</id>
      <name>Price</name>
      <observability>1</observability>
    </Attribute>
    <Attribute>
      <id>2</id>
      <name>Environment</name>
      <observability>0.1</observability>
    </Attribute>
    <Attribute>
      <id>3</id>
      <name>Brand</name>
      <observability>0.6</observability>
    </Attribute>
    <Attribute>
      <id>4</id>
      <name>Consumption</name>
      <observability>0.6</observability>
    </Attribute>
    <Attribute>
      <id>5</id>
      <name>Raw material</name>
      <observability>0.1</observability>
    </Attribute>
  </attributes>
  <producers>
    <Producer>
      <id>0</id>
      <name>Conventional non-branded fuel producer</name>
      <products class="list">
        <FuelProduct>
          <id>1</id>
          <name>Conventional non-branded fuel</name>
```

```
      <attributeValues class="map">
        <entry>
          <!-- Quality -->
          <Attribute reference="../../../../../../../attributes/Attribute" />
          <double>0</double>
        </entry>
        <entry>
          <!-- Price is set in pricingPolicy.xml (setting here is irrelevant) -->
          <Attribute reference="../../../../../../../attributes/Attribute[2]" />
          <double>1.2</double>
        </entry>
        <entry>
          <!-- Environment -->
          <Attribute reference="../../../../../../../attributes/Attribute[3]" />
          <double>0</double>
        </entry>
        <entry>
          <!-- Brand -->
          <Attribute reference="../../../../../../../attributes/Attribute[4]" />
          <double>0</double>
        </entry>
        <entry>
          <!-- Consumption -->
          <Attribute reference="../../../../../../../attributes/Attribute[5]" />
          <double>1</double>
        </entry>
        <entry>
          <!-- Raw material (0 = crude oil) -->
          <Attribute reference="../../../../../../../attributes/Attribute[6]" />
          <double>0</double>
        </entry>
      </attributeValues>
      <color>
        <red>0</red>
        <green>0</green>
        <blue>255</blue>
        <alpha>255</alpha>
      </color>
      <innovation>false</innovation>
      <baseRangeMultiplier>1.0</baseRangeMultiplier>
    </FuelProduct>

    <FuelProduct>
      <id>2</id>
      <name>Conventional branded fuel</name>
      <attributeValues class="map">
        <entry>
          <!-- Quality -->
          <Attribute reference="../../../../../../../attributes/Attribute" />
          <double>0</double>
        </entry>
        <entry>
          <!-- Price is set in pricingPolicy.xml (setting here is irrelevant) -->
          <Attribute reference="../../../../../../../attributes/Attribute[2]" />
          <double>1.22</double>
        </entry>
        <entry>
          <!-- Environment -->
          <Attribute reference="../../../../../../../attributes/Attribute[3]" />
          <double>0</double>
        </entry>
        <entry>
          <!-- Brand -->
          <Attribute reference="../../../../../../../attributes/Attribute[4]" />
          <double>1</double>
        </entry>
        <entry>
          <!-- Consumption -->
          <Attribute reference="../../../../../../../attributes/Attribute[5]" />
          <double>1</double>
        </entry>
```

```
            <entry>
              <!-- Raw material (0 = crude oil) -->
              <Attribute reference="../../../../../../../attributes/Attribute[6]" />
              <double>0</double>
            </entry>
          </attributeValues>
          <color>
            <red>0</red>
            <green>0</green>
            <blue>0</blue>
            <alpha>255</alpha>
          </color>
          <innovation>false</innovation>
          <baseRangeMultiplier>1.0</baseRangeMultiplier>
        </FuelProduct>

        <FuelProduct>
          <id>3</id>
          <name>Premium fuel branded (conventional)</name>
          <attributeValues class="map">
            <entry>
              <!-- Quality -->
              <Attribute reference="../../../../../../../attributes/Attribute" />
              <double>1</double>
            </entry>
            <entry>
              <!-- Price -->
              <!-- Price is set in pricingPolicy.xml (setting here is irrelevant) -->
              <Attribute reference="../../../../../../../attributes/Attribute[2]" />
              <double>1.35</double>
            </entry>
            <entry>
              <!-- Environment -->
              <Attribute reference="../../../../../../../attributes/Attribute[3]" />
              <double>0</double>
            </entry>
            <entry>
              <!-- Brand -->
              <Attribute reference="../../../../../../../attributes/Attribute[4]" />
              <double>1</double>
            </entry>
            <entry>
              <!-- Consumption -->
              <Attribute reference="../../../../../../../attributes/Attribute[5]" />
              <double>1</double>
            </entry>
            <entry>
              <!-- Raw material (0 = crude oil) -->
              <Attribute reference="../../../../../../../attributes/Attribute[6]" />
              <double>0</double>
            </entry>
          </attributeValues>
          <color>
            <red>139</red>
            <green>0</green>
            <blue>0</blue>
            <alpha>255</alpha>
          </color>
          <innovation>true</innovation>
          <baseRangeMultiplier>1.0</baseRangeMultiplier>
        </FuelProduct>
      </products>
    </Producer>
    <Producer>
      <id>1</id>
      <name>BioFIT Producer</name>
      <products class="list">
        <FuelProduct>
          <id>4</id>
          <name>BioFIT</name>
          <attributeValues class="map">
```

```
          <entry>
            <!-- Quality -->
            <Attribute reference="../../../../../../../attributes/Attribute" />
            <double>1</double>
          </entry>
          <entry>
            <!-- Price -->
            <Attribute reference="../../../../../../../attributes/Attribute[2]" />
            <!-- Price is set in pricingPolicy.xml -->
            <double>1.3</double>
          </entry>
          <entry>
            <!-- Environment -->
            <Attribute reference="../../../../../../../attributes/Attribute[3]" />
            <double>1</double>
          </entry>
          <entry>
            <!-- Brand -->
            <Attribute reference="../../../../../../../attributes/Attribute[4]" />
            <double>1</double>
          </entry>
          <entry>
            <!-- Consumption -->
            <Attribute reference="../../../../../../../attributes/Attribute[5]" />
            <double>0.95</double>
          </entry>
          <entry>
            <!-- Raw material (1 = bio mass) -->
            <Attribute reference="../../../../../../../attributes/Attribute[6]" />
            <double>1.0</double>
          </entry>
        </attributeValues>
        <color>
          <red>0</red>
          <green>100</green>
          <blue>0</blue>
          <alpha>255</alpha>
        </color>
        <innovation>true</innovation>
        <baseRangeMultiplier>1.05</baseRangeMultiplier>
      </FuelProduct>
    </products>
  </Producer>
</producers>

<noConsumerAgents>10000</noConsumerAgents>

<consumerAgentsDataFileName>../../../common/consumerDataHighestUtilityHistoryPOSSelection.xml</
    consumerAgentsDataFileName>

<partialUtilityFunctionParameters class="map">
  <entry>
    <!-- Quality -->
    <Attribute reference="../../../attributes/Attribute" />
    <PartialUtilityFunctionParameter>
      <monotonuous>true</monotonuous>
      <increasing>true</increasing>
    </PartialUtilityFunctionParameter>
  </entry>
  <entry>
    <!-- Price -->
    <Attribute reference="../../../attributes/Attribute[2]" />
    <PartialUtilityFunctionParameter>
      <monotonuous>true</monotonuous>
      <increasing>false</increasing>
    </PartialUtilityFunctionParameter>
  </entry>
  <entry>
    <!-- Environment -->
    <Attribute reference="../../../attributes/Attribute[3]" />
    <PartialUtilityFunctionParameter>
```

```xml
          <monotonuous>true</monotonuous>
          <increasing>true</increasing>
        </PartialUtilityFunctionParameter>
      </entry>
      <entry>
        <!-- Brand -->
        <Attribute reference="../../../attributes/Attribute[4]" />
        <PartialUtilityFunctionParameter>
          <monotonuous>false</monotonuous>
          <increasing>true</increasing><!-- not relevant -->
        </PartialUtilityFunctionParameter>
      </entry>
      <entry>
        <!-- Consumption -->
        <Attribute reference="../../../attributes/Attribute[5]" />
        <PartialUtilityFunctionParameter>
          <monotonuous>true</monotonuous>
          <increasing>false</increasing>
        </PartialUtilityFunctionParameter>
      </entry>
      <entry>
        <!-- Raw material -->
        <Attribute reference="../../../attributes/Attribute[6]" />
        <PartialUtilityFunctionParameter>
          <monotonuous>false</monotonuous>
          <increasing>true</increasing>
        </PartialUtilityFunctionParameter>
      </entry>
    </partialUtilityFunctionParameters>

    <productInformationModel>HISTOGRAM_MODEL</productInformationModel>
    <productInformationParameters class="HistogramProductInformationParameters">
      <decayFactor>0.2</decayFactor>
      <categories>10</categories>
    </productInformationParameters>

    <!--  Communication parameters -->
    <communicationInterarrivalTimeDistribution class="PoissonDistribution">
          <mean>30.0</mean>
      </communicationInterarrivalTimeDistribution>
      <numberOfTopicsPerCommunicationEventDistribution class="NormalDistribution">
          <mean>2.0</mean>
          <standardDeviation>1.0</standardDeviation>
      </numberOfTopicsPerCommunicationEventDistribution>
      <credibilityDistribution class="UniformDistributionParameter">
          <min>0.5</min>
          <max>0.5</max>
      </credibilityDistribution>

        <productAwarenessShare class="map">
          <entry>
            <!-- Conventional fuel non-branded -->
            <FuelProduct reference="../../../producers/Producer/products/FuelProduct" />
            <double>1</double>
          </entry>
          <entry>
            <!-- Conventional fuel branded -->
            <FuelProduct reference="../../../producers/Producer/products/FuelProduct[2]" />
            <double>1</double>
          </entry>
          <entry>
            <!-- Premium fuel known by 0% -->
            <FuelProduct reference="../../../producers/Producer/products/FuelProduct[3]" />
            <double>0</double>
          </entry>
          <entry>
            <!--  Nobody is aware of 2G biofuel at the beginning -->
            <FuelProduct reference="../../../producers/Producer[2]/products/FuelProduct" />
            <double>0</double>
          </entry>
        </productAwarenessShare>
```

```

    <attributeAwarenessShare class="map">
      <!-- Awareness of attribute "quality" -->
      <entry>
        <Attribute reference="../../../attributes/Attribute" />
        <double>0</double>
      </entry>
      <!-- Awareness of attribute "price" -->
      <entry>
        <Attribute reference="../../../attributes/Attribute[2]" />
        <double>1</double>
      </entry>
      <!-- Awareness of attribute "environment" -->
      <entry>
        <Attribute reference="../../../attributes/Attribute[3]" />
        <double>0</double>
      </entry>
      <!-- Awareness of attribute "brand" -->
      <entry>
        <Attribute reference="../../../attributes/Attribute[4]" />
        <double>1</double>
      </entry>
      <!-- Awareness of attribute "consumption" -->
      <entry>
        <Attribute reference="../../../attributes/Attribute[5]" />
        <double>0</double>
      </entry>
      <!-- Awareness of attribute "raw material" -->
      <entry>
        <Attribute reference="../../../attributes/Attribute[6]" />
        <double>0</double>
      </entry>
    </attributeAwarenessShare>


    <initialAttributeValuations class="map">
      <!-- Conventional fuel non-branded -->
      <entry>
        <FuelProduct reference="../../../producers/Producer/products/FuelProduct" />
        <map>
          <!--  Price -->
          <entry>
            <Attribute reference="../../../../../attributes/Attribute[2]" />
            <UniformDistributionParameter>
              <min>1.2</min>
              <max>1.2</max>
            </UniformDistributionParameter>
          </entry>
          <!-- Brand -->
          <entry>
            <Attribute reference="../../../../../attributes/Attribute[4]" />
            <UniformDistributionParameter>
              <min>0</min>
              <max>0</max>
            </UniformDistributionParameter>
          </entry>
        </map>
      </entry>

      <!-- Conventional fuel branded-->
      <entry>
        <FuelProduct reference="../../../producers/Producer/products/FuelProduct[2]" />
        <map>
          <!--  Price -->
          <entry>
            <Attribute reference="../../../../../attributes/Attribute[2]" />
            <UniformDistributionParameter>
              <min>1.22</min>
              <max>1.22</max>
            </UniformDistributionParameter>
          </entry>
```

```
          <!-- Brand -->
          <entry>
            <Attribute reference="../../../../../attributes/Attribute[4]" />
            <UniformDistributionParameter>
              <min>1</min>
              <max>1</max>
            </UniformDistributionParameter>
          </entry>
        </map>
      </entry>

      <!--  Premium fuel -->
      <entry>
      <FuelProduct reference="../../../producers/Producer/products/FuelProduct[3]" />
        <map>
          <!-- "quality"  -->
          <entry>
            <Attribute reference="../../../../../attributes/Attribute" />
            <UniformDistributionParameter>
              <min>0</min>
              <max>0</max>
            </UniformDistributionParameter>
          </entry>

          <!-- "price"  -->
          <entry>
            <Attribute reference="../../../../../attributes/Attribute[2]" />
            <UniformDistributionParameter>
              <min>1</min>
              <max>1</max>
            </UniformDistributionParameter>
          </entry>
          <!-- "environment"  -->
          <entry>
            <Attribute reference="../../../../../attributes/Attribute[3]" />
            <UniformDistributionParameter>
              <min>0</min>
              <max>0</max>
            </UniformDistributionParameter>
          </entry>
          <!-- "brand"  -->
          <entry>
            <Attribute reference="../../../../../attributes/Attribute[4]" />
            <UniformDistributionParameter>
              <min>0</min>
              <max>0</max>
            </UniformDistributionParameter>
          </entry>
          <!-- "consumption"  -->
          <entry>
            <Attribute reference="../../../../../attributes/Attribute[5]" />
            <UniformDistributionParameter>
              <min>1</min>
              <max>1</max>
            </UniformDistributionParameter>
          </entry>
          <!-- "raw material"  -->
          <entry>
            <Attribute reference="../../../../../attributes/Attribute[6]" />
            <UniformDistributionParameter>
              <min>0</min>
              <max>0</max>
            </UniformDistributionParameter>
          </entry>
      </map>
      </entry>
    <!-- BtL-fuel -->
    <entry>
      <FuelProduct reference="../../../producers/Producer[2]/products/FuelProduct" />
        <map>
          <!-- "quality"  -->
```

```
      <entry>
        <Attribute reference="../../../../../attributes/Attribute" />
        <UniformDistributionParameter>
          <min>0</min>
          <max>0</max>
        </UniformDistributionParameter>
      </entry>

      <!-- "price" -->
      <entry>
        <Attribute reference="../../../../../attributes/Attribute[2]" />
        <UniformDistributionParameter>
          <min>1</min>
          <max>1</max>
        </UniformDistributionParameter>
      </entry>
      <!-- "environment" -->
      <entry>
        <Attribute reference="../../../../../attributes/Attribute[3]" />
        <UniformDistributionParameter>
          <min>0</min>
          <max>0</max>
        </UniformDistributionParameter>
      </entry>
      <!-- "brand" -->
      <entry>
        <Attribute reference="../../../../../attributes/Attribute[4]" />
        <UniformDistributionParameter>
          <min>0.5</min>
          <max>0.5</max>
        </UniformDistributionParameter>
      </entry>
      <!-- "consumption" -->
      <entry>
        <Attribute reference="../../../../../attributes/Attribute[5]" />
        <UniformDistributionParameter>
          <min>1</min>
          <max>1</max>
        </UniformDistributionParameter>
      </entry>
      <!-- "raw material" -->
      <entry>
        <Attribute reference="../../../../../attributes/Attribute[6]" />
        <UniformDistributionParameter>
          <min>0</min>
          <max>0</max>
        </UniformDistributionParameter>
      </entry>
  </map>
  </entry>
</initialAttributeValuations>


<marketingCommunicationTypeImpactFactors class="map">
  <entry>
    <MarketingCommunicationTypeParam>
    <name>POS_advertisement</name>
    </MarketingCommunicationTypeParam>
    <UniformDistributionParameter>
      <min>0.2</min>
      <max>0.2</max>
    </UniformDistributionParameter>
  </entry>
  <entry>
    <MarketingCommunicationTypeParam>
      <name>POS_priceAnnouncement</name>
    </MarketingCommunicationTypeParam>
    <UniformDistributionParameter>
      <min>1</min>
      <max>1</max>
    </UniformDistributionParameter>
```

```xml
        </entry>
      </marketingCommunicationTypeImpactFactors>
  <pointsOfSale>
    <PointOfSale>
        <id>15079898</id>
        <name>BP</name>
        <location>
          <x>48.1927168</x>
          <y>16.2776905</y>
          <z>0</z>
        </location>
        <attractiveness>1</attractiveness>
      <brand>true</brand>
      <pricingStrategy>SIMPLE_MARKUP</pricingStrategy>
      <markup>0</markup>
    </PointOfSale>
      ...
    [1571 points of sale]
      ...
  </pointsOfSale>

  <GISModel>true</GISModel>
  <geographyShapeFileName>../../../common/geodata/population_2500m/population_2500m.shp</geographyShapeFileName>
  <populationFieldName>HWS0101200</populationFieldName>
</ScenarioWithIndividualAgentData>
```

Listing A.6: `scenario.xml`

Consumer data

```xml
<ConsumerAgentsInitializationData>
  <consumerAgentData>
    <agent>
      <id>4662081</id>
      <kilometersPerYear>40000.0</kilometersPerYear>
      <tankSize>55</tankSize>
      <consumption>7.0</consumption>
      <pointOfSaleSelection class="NearestPOSWithHistoryPOSSelectionParameter">
        <purchHistSize>4</purchHistSize>
        <proximityExponent>5.0</proximityExponent>
        <pRecent>0.8</pRecent>
      </pointOfSaleSelection>
      <partialUtilities class="map">
        <entry>
          <int>0</int>
          <map>
            <entry>
              <double>0.0</double>
              <double>0.0</double>
            </entry>
            <entry>
              <double>1.0</double>
              <double>0.01</double>
            </entry>
          </map>
        </entry>
        <entry>
          <int>1</int>
          <map>
            <entry>
              <double>1.3</double>
              <double>0.206</double>
            </entry>
            <entry>
              <double>1.1</double>
              <double>0.59</double>
            </entry>
```

```
          <entry>
            <double>1.4</double>
            <double>0.0</double>
          </entry>
          <entry>
            <double>1.2</double>
            <double>0.392</double>
          </entry>
          <entry>
            <double>1.0</double>
            <double>0.78</double>
          </entry>
        </map>
      </entry>
      <entry>
        <int>2</int>
        <map>
          <entry>
            <double>0.0</double>
            <double>0.0</double>
          </entry>
          <entry>
            <double>1.0</double>
            <double>0.0</double>
          </entry>
        </map>
      </entry>
      <entry>
        <int>3</int>
        <map>
          <entry>
            <double>0.0</double>
            <double>0.0</double>
          </entry>
          <entry>
            <double>1.0</double>
            <double>0.0</double>
          </entry>
        </map>
      </entry>
      <entry>
        <int>4</int>
        <map>
          <entry>
            <double>0.95</double>
            <double>0.0</double>
          </entry>
          <entry>
            <double>1.0</double>
            <double>0.0</double>
          </entry>
          <entry>
            <double>0.9</double>
            <double>0.0</double>
          </entry>
        </map>
      </entry>
      <entry>
        <int>5</int>
        <map>
          <entry>
            <double>0.0</double>
            <double>0.0</double>
          </entry>
          <entry>
            <double>1.0</double>
            <double>0.0</double>
          </entry>
        </map>
      </entry>
    </partialUtilities>
```

```xml
    </agent>

    <agent>
      ...
    </agent>
    ...
    [survey data from 1000 respondents (total)]
  </consumerAgentData>
</ConsumerAgentsInitializationData>
```

Listing A.7: `consumerData.xml`

Pricing policy

```xml
<!-- productID -> sorted map of price changes for the product -->
<PricingPolicy>
  <pricing class="map">
    <!-- Conventional fuel non-branded -->
    <entry>
      <int>1</int>
      <tree-map>
        <no-comparator/>
        <entry>
          <double>0.0</double>
          <double>1.2</double>
        </entry>
      </tree-map>
    </entry>

    <!-- Conventional fuel branded -->
    <entry>
      <int>2</int>
      <tree-map>
        <no-comparator/>
        <entry>
          <double>0.0</double>
          <double>1.22</double>
        </entry>
      </tree-map>
    </entry>

    <!-- Conventional premium fuel -->
    <entry>
      <int>3</int>
      <tree-map>
        <no-comparator/>
        <entry>
          <double>0.0</double>
          <double>1.35</double>
        </entry>
      </tree-map>
    </entry>

    <!-- BtL-Fuel -->
    <entry>
      <int>4</int>
      <tree-map>
        <no-comparator/>
        <entry>
          <double>0.0</double>
          <double>1.3</double>
        </entry>
      </tree-map>
    </entry>
  </pricing>
</PricingPolicy>
```

Listing A.8: `pricingPolicy.xml`

Rollout policy

```xml
<?xml version="1.0"?>
<RolloutPolicy>
  <posLaunch class="map">
    <!--  Conventional non-branded introduced at all 757 non-branded gas stations @ t=0 -->
    <entry>
      <int>1</int>
      <map>
        <entry>
          <double>0.0</double>
          <list>
            <int>20921198</int>
                ...
             [757 points of sale]
                ...
          </list>
        </entry>
      </map>
    </entry>
    <!--  Conventional branded introduced at all 814 branded gas stations @ t=0 -->
    <entry>
      <int>2</int>
      <map>
        <entry>
          <double>0.0</double>
          <list>
            <int>15079898</int>
                ...
             [814 points of sale]
                ...
          </list>
        </entry>
      </map>
    </entry>
    <!-- Premium fuels only available at 548 gas stations @ t=750 -->
    <entry>
      <int>3</int>
      <map>
        <entry>
          <double>750.0</double>
          <list>
            <int>15079898</int>
                ...
             [548 points of sale]
                ...
          </list>
        </entry>
      </map>
    </entry>
    <!--  BtL-fuel only available at gas stations of a major operator-->
    <entry>
      <int>4</int>
      <map>
        <entry>
          <double>1500.0</double>
          <list>
            <int>15337840</int>
                ...
             [189 points of sale]
                ...
          </list>
        </entry>
      </map>
    </entry>
  </posLaunch>
</RolloutPolicy>
```

Listing A.9: `rolloutPolicy.xml`

Communication policy

```
<CommunicationPolicy>
  <communicationActivities class="list">
  <!-- Announce price of conventional unbranded fuel -->
    <PosCommunicationActivity>
      <communicationActivityId>1</communicationActivityId>
      <productID>1</productID>
      <communicatedAttributeValues class="map">
        <!--  Price -->
        <entry>
          <int>1</int>
          <double>1.2</double>
        </entry>
      </communicatedAttributeValues>
      <type>
        <name>POS_priceAnnouncement</name>
      </type>
      <timeFrom>0.0</timeFrom>
      <timeTill>5000.0</timeTill>
      <pMakeAware>0</pMakeAware>
    <pExposureWhenAware>0.7</pExposureWhenAware>
    <pointsOfSale>
      <int>20921198</int>
           ...
      [757 points of sale]
           ...
    </pointsOfSale>
    </PosCommunicationActivity>

  <!-- Announce price of conventional branded fuel -->
    <PosCommunicationActivity>
      <communicationActivityId>2</communicationActivityId>
      <productID>2</productID>
      <communicatedAttributeValues class="map">
        <!--  Price -->
        <entry>
          <int>1</int>
          <double>1.22</double>
        </entry>
      </communicatedAttributeValues>
      <type>
        <name>POS_priceAnnouncement</name>
      </type>
      <timeFrom>0.0</timeFrom>
      <timeTill>5000.0</timeTill>
      <pMakeAware>0</pMakeAware>
    <pExposureWhenAware>0.7</pExposureWhenAware>
    <pointsOfSale>
      <int>15079898</int>
           ...
      [814 points of sale]
           ...
      </pointsOfSale>
    </PosCommunicationActivity>

    <!-- Introduce premium fuel -->
    <PosCommunicationActivity>
      <communicationActivityId>3</communicationActivityId>
      <productID>3</productID>
      <communicatedAttributeValues class="map">
        <!--  Quality -->
        <entry>
          <int>0</int>
          <double>1.0</double>
        </entry>
        <!--  Price -->
        <entry>
          <int>1</int>
          <double>1.35</double>
        </entry>
```

```
        <!--  Brand -->
        <entry>
          <int>3</int>
          <double>1.0</double>
        </entry>
      </communicatedAttributeValues>
      <type>
        <name>POS_advertisement</name>
      </type>
      <timeFrom>750.0</timeFrom>
      <timeTill>780.0</timeTill>
      <pMakeAware>0.05</pMakeAware>
    <pExposureWhenAware>0.1</pExposureWhenAware>
    <pointsOfSale>
        <int>15079898</int>
           ...
      [548 points of sale]
           ...
    </pointsOfSale>
    </PosCommunicationActivity>


    <!-- Introduce biofuel -->
    <PosCommunicationActivity>
      <communicationActivityId>4</communicationActivityId>
      <productID>4</productID>
      <communicatedAttributeValues class="map">
        <!--  Quality -->
        <entry>
          <int>0</int>
          <double>1.0</double>
        </entry>
    <!-- Environment -->
        <entry>
          <int>2</int>
          <double>1.0</double>
        </entry>
        <!--  Brand -->
        <entry>
          <int>3</int>
          <double>1.0</double>
        </entry>
        <!-- Consumption -->
        <entry>
          <int>4</int>
          <double>0.95</double>
        </entry>
        <!--  Raw material -->
        <entry>
          <int>5</int>
          <double>1.0</double>
        </entry>
        <!--  Price -->
        <entry>
          <int>1</int>
          <double>1.3</double>
        </entry>
      </communicatedAttributeValues>
      <type>
        <name>POS_advertisement</name>
      </type>
      <timeFrom>1500.0</timeFrom>
      <timeTill>1530.0</timeTill>
      <pMakeAware>0.05</pMakeAware>
      <pExposureWhenAware>0.1</pExposureWhenAware>
    <pointsOfSale>
    <int>15337840</int>
         ...
    [189 points of sale]
         ...
    </pointsOfSale>
```

```
    </PosCommunicationActivity>
  </communicationActivities>
</CommunicationPolicy>
```

Listing A.10: `communicationPolicy.xml`

A.3. Example simulation output

Simulation log

```
 INFO Quasimodi                    Starting in batch mode
 INFO Quasimodi                    Reading batch run file /storage/diss_newComm/singleRunDebugLog/pricing_13/assignment_1299961164/batch.xml
 INFO Quasimodi                    5 runs will be performed
 INFO Quasimodi                    Starting simulation run 1/5. Runtime so far: 0:00:01.195
Remaining space: 328 GB

 INFO ShapeFileLoader              Reading shapefile from /storage/diss_newComm/singleRunDebugLog/pricing_13/assignment_1299961164/../../../common/geodata/population_2500m/population_2500m.shp
 INFO  Geography                   Read population of 13997 gis cells.
DEBUG StaticConsumerLocationAssigner Assigning agent 44671243 to location (9.773931016496102, 47.46792817118052, NaN)
DEBUG StaticConsumerLocationAssigner Assigning agent 34672731 to location (16.732238447321294, 48.364243406022084, NaN)
  ... [Location assignment for 10.000 consumer agents] ...
DEBUG PosSelectorFactory           Creating nearest POS with utility history point of sale selector for agent 54662674. Parameters: purchHistSize=4, pRecent=0.6, proximity exponent=1.0
  ... [Initialization of point of sale selection method for 10.000 consumer agents] ...
 INFO RolloutEvent                 @0.0: Product Conventional branded fuel becomes available at 814 point(s) of sale
DEBUG RolloutEvent                 Product Conventional branded fuel becomes available at POS OMV
DEBUG RolloutEvent                 Product Conventional branded fuel becomes available at POS Shell
  ... [Execution of rollout event for conventional branded fuel] ...
 INFO RolloutEvent                 @0.0: Product Conventional non-branded fuel becomes available at 757 point(s) of sale
DEBUG RolloutEvent                 Product Conventional non-branded fuel becomes available at POS JET
DEBUG RolloutEvent                 Product Conventional non-branded fuel becomes available at POS MOL
  ... [Execution of rollout event for conventional non-branded fuel] ...
 INFO StartPosCommunicationActivity Starting pos communication activity 1 at 757 points of sale
 INFO StartPosCommunicationActivity Starting pos communication activity 2 at 814 points of sale
 INFO QuasimodiSimState            Setting up chart generators
  ...
DEBUG GasStopEvent                 @0.0018592742799674782: Gas stop by consumer 24662152
DEBUG ConsumerAgent                Agent 24662152 chose POS 769416016 for gas stop.
DEBUG PosCommunicationActivity     Agent exposed to 24662152 POS marketing activity 2
DEBUG ConsumerAgent                Marketing communication to agent 24662152, who has a prior valuation of 0.015 for product Conventional branded fuel
DEBUG ConsumerAgent                New valuation: 0.015
DEBUG ConsumerAgent                Agent 24662152 purchased Conventional branded fuel
  ...
 INFO StartPosCommunicationActivity Starting pos communication activity 2 at 814 points of sale
  ...
 INFO RolloutEvent                 @750.0: Product Premium fuel branded (conventional) becomes available at 548 point(s) of sale
 INFO StartPosCommunicationActivity Starting pos communication activity 3 at 548 points of sale
 INFO StartPosCommunicationActivity Stopping pos communication activity 3 at 548 points of sale
  ...
 DEBUG PosCommunicationActivity  Agent exposed to 32662735 POS marketing activity 2
  ...
 INFO RolloutEvent                 @1500.0: Product BioFIT becomes available at 189 point(s) of sale
 INFO StartPosCommunicationActivity Starting pos communication activity 4 at 189 points of sale
 INFO StartPosCommunicationActivity Stopping pos communication activity 4 at 189 points of sale
  ...
 DEBUG PosCommunicationActivity  Agent exposed to 64662755 POS marketing activity 4
  ...
```

```
DEBUG AltPeriodicCommunication  Agent A adding topic (BioFIT,Environment). Utility last time: <UNAWARE
    >, now: 0.041999999999999996
DEBUG AltPeriodicCommunication  Agent A adding topic (BioFIT,Raw material). Utility last time: <
    UNAWARE>, now: 0.17500000000000032
  ...
DEBUG GasStopEvent              @1503.5697360696581: Gas stop by consumer 74664989
DEBUG PosCommunicationActivity  Agent exposed to 4677795 POS marketing activity 4
DEBUG ConsumerAgent             Agent 4677795 purchased BioFIT
  ...
INFO QuasimodiSimState         Simulation run complete
INFO QuasimodiSimState         Generating charts
INFO QuasimodiSimState         Killing simulation
INFO Quasimodi                 Simulation run complete. Time: 0:23:19.359

  ...
  [Replications]
  ...

INFO Quasimodi                 Total runtime: 1:55:59.030
```

Listing A.11: `simulation.log` (output level: DEBUG)

Attribute awareness (CSV)

```
time,agentID,attributeID,aware
0.0,4662081,1,true
0.0,4662081,3,true
0.0,4662083,1,true
0.0,4662083,3,true
0.0,4662086,1,true
0.0,4662086,3,true
0.0,4662088,1,true
0.0,4662088,3,true
0.0,4662090,1,true
0.0,4662090,3,true
0.0,4662091,1,true
0.0,4662091,3,true
0.0,4662092,1,true
0.0,4662092,3,true
0.0,4662093,1,true
  ...
```

Listing A.12: `attributeAwareness.csv`

Information flow (CSV)

```
time,toAgentID,fromAgentID,productID,attributeID,oldValuation,correspondentValuation,newValuation
2089.6510534973995,94664837,4663000,4,1,1.141358942188399,1.1499999612177059,1.1428288215916964
2089.6510534973995,4663000,94664837,4,1,1.1499999612177059,1.141358942188399,1.1499999999976493
2089.6510534973995,94664837,4663000,4,0,0.7712947183091554,0.8500000000000094,0.8085848908634196
2089.6510534973995,4663000,94664837,4,0,0.8500000000000094,0.7712947183091554,0.754854727926477 3
2089.653577407774,24664991,4664863,4,1,1.1318892300144785,1.149999999999038,1.1377440443242535
2089.653577407774,4664863,24664991,4,1,1.149999999999038,1.1318892300144785,1.149999999999846
2089.6547580958495,94662581,64664668,4,0,0.6489871928819426,0.11449194564407221,0.35322690265491824
2089.6547580958495,64664668,94662581,4,0,0.11449194564407221,0.6489871928819426,0.40340296748227955
2089.6547580958495,94662581,64664668,4,2,0.5602698337139536,0.05,0.14261840220996183
2089.6547580958495,64664668,94662581,4,2,0.05,0.5602698337139536,0.5499999999999999
  ...
```

Listing A.13: `informationFlow.csv`

Product awareness (CSV)

```
time,agentID,productID,aware
0.0,4662081,1,true
0.0,4662081,2,true
0.0,4662083,1,true
0.0,4662083,2,true
0.0,4662086,1,true
0.0,4662086,2,true
0.0,4662088,1,true
0.0,4662088,2,true
0.0,4662090,1,true
0.0,4662090,2,true
0.0,4662091,1,true
0.0,4662091,2,true
0.0,4662092,1,true
   ...
```

Listing A.14: `productAwareness.csv`

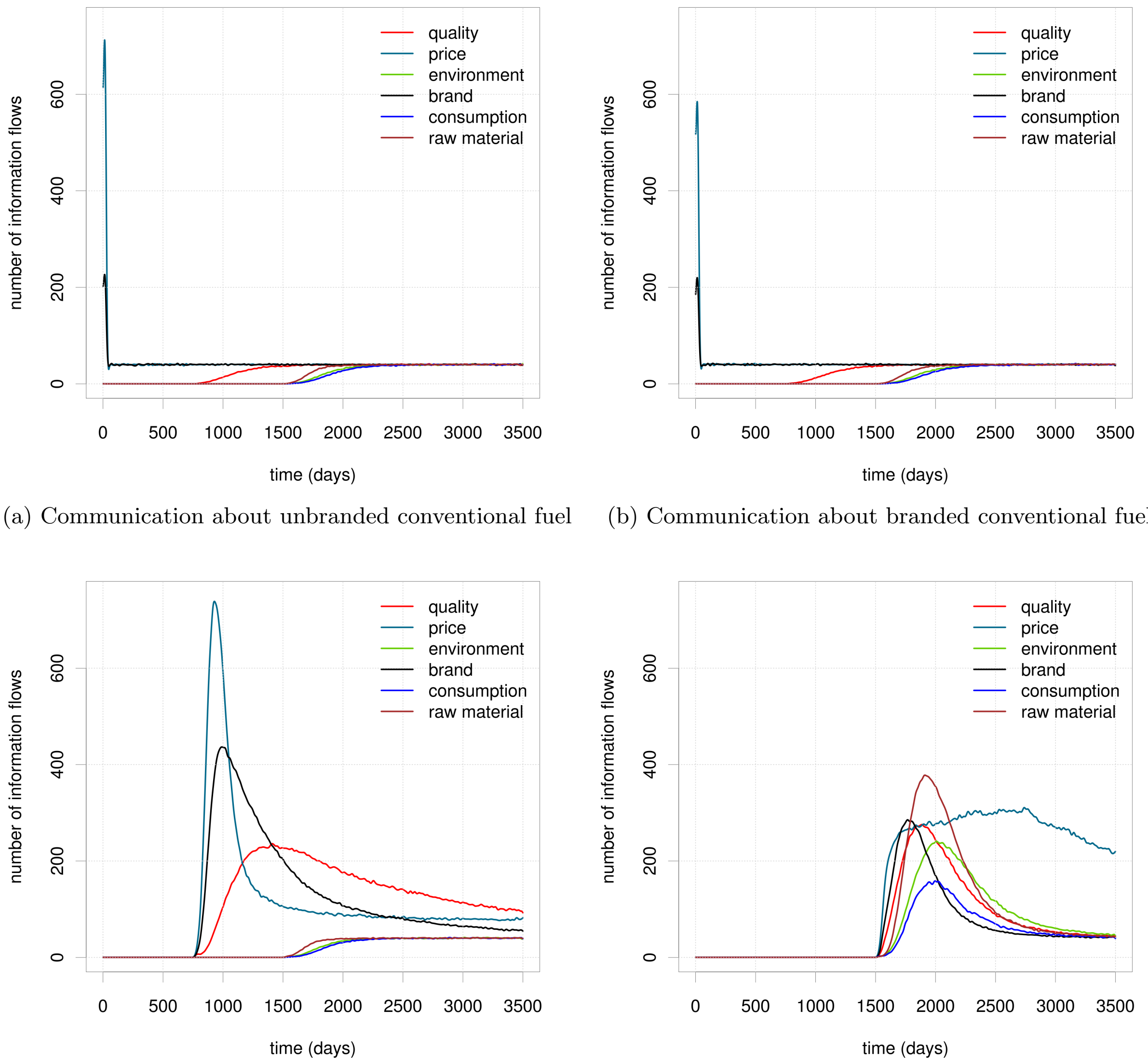
Sales (CSV)

```
time,agentID,productID,posID,quantity,totalPrice
2.559809888491715E-4,64662305,2,86059504,65.0,79.3
0.0018592742799674782,24662152,2,769416016,45.0,54.9
0.003976353465339456,24662600,1,72465683,50.0,60.0
0.005177033692159173,54665113,2,224418750,60.0,73.2
0.005802203524685343,44664793,1,623425717,48.0,57.599999999999994
0.006891600553424425,94663063,1,312980012,55.0,66.0
0.007132818190139541,54664716,1,248206408,70.0,84.0
0.008626091111700079,14665437,1,31238760,50.0,60.0
0.011617636243631517,84662959,2,325022131,50.0,61.0
0.012575048896151561,94678590,1,302331426,45.0,54.0
0.013655154375750983,54682050,1,434315406,55.0,66.0
0.01613656189667458,54682235,1,86111599,50.0,60.0
0.017373385976408792,94665251,1,573126117,35.0,42.0
0.02401859587967749,34662633,2,248102690,56.0,68.32
0.02443089678426771,54663005,2,255993689,60.0,73.2
...
```

Listing A.15: `sales.csv`

A.4. Additional simulation result plots

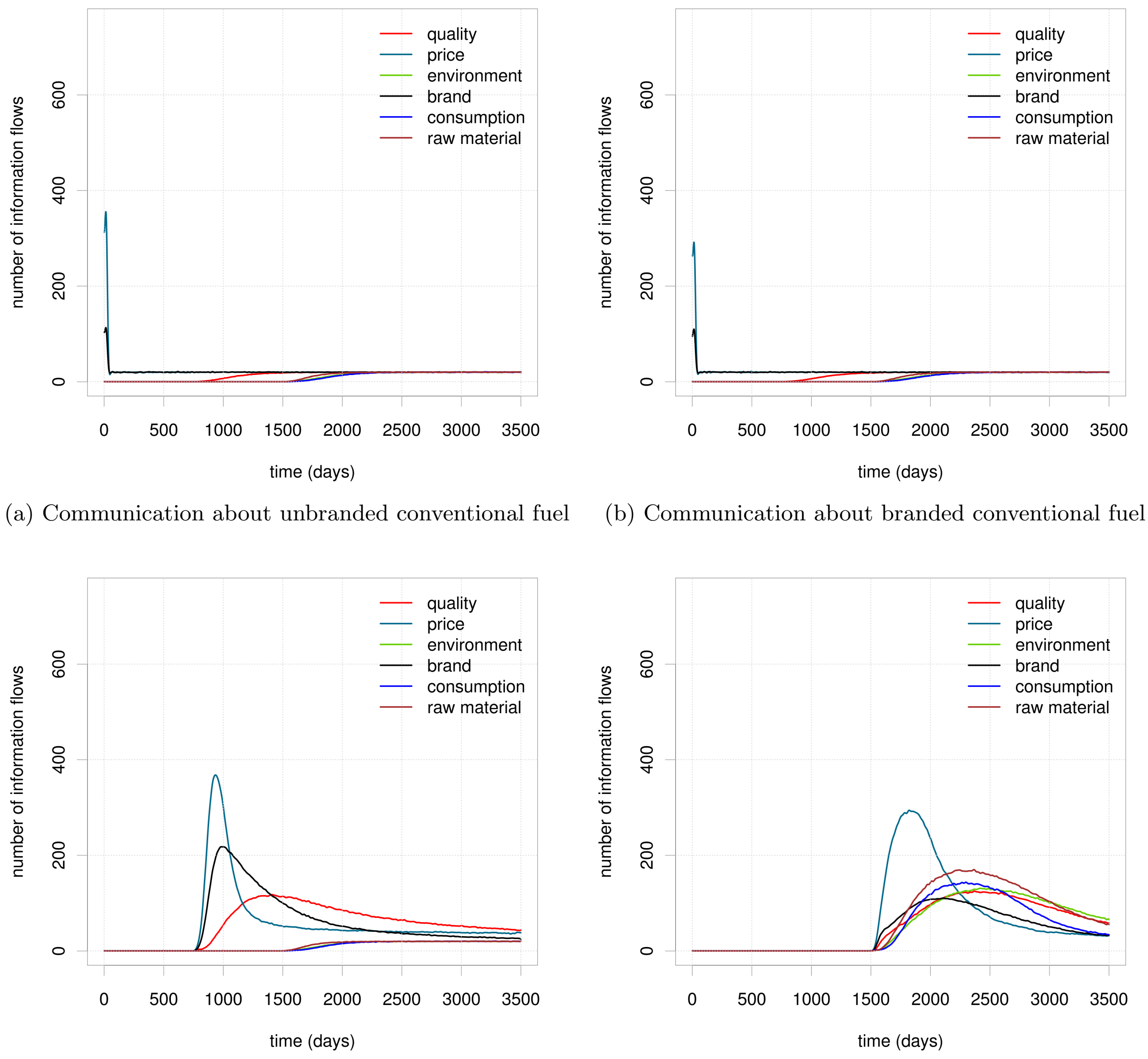
A.4.1. Base scenario



(a) Communication about unbranded conventional fuel (b) Communication about branded conventional fuel

(c) Communication about premium fuel (d) Communication about BtL-fuel

Figure A.1.: Number of communication events by attributes over time for $p_{BtL} = 1.2$ (5 consumer assignments to nodes x 10 random seeds = 50 replications)



(a) Communication about unbranded conventional fuel

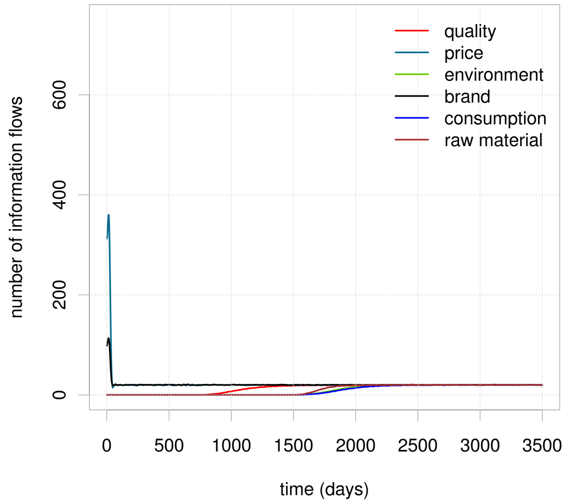
(b) Communication about branded conventional fuel

(c) Communication about premium fuel

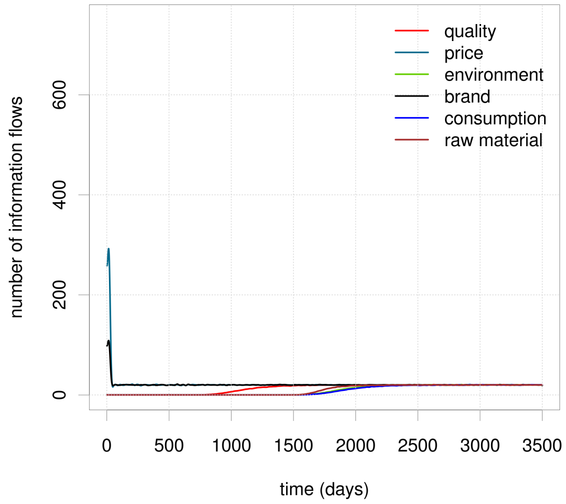
(d) Communication about BtL-fuel

Figure A.2.: Number of communication events by attributes over time for $p_{BtL} = 1.4$ (5 consumer assignments to nodes x 10 random seeds = 50 replications)

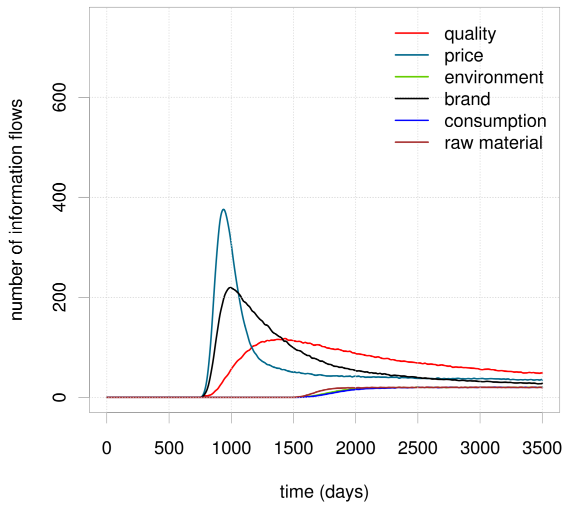
A.4.2. Scenario with discontinuation



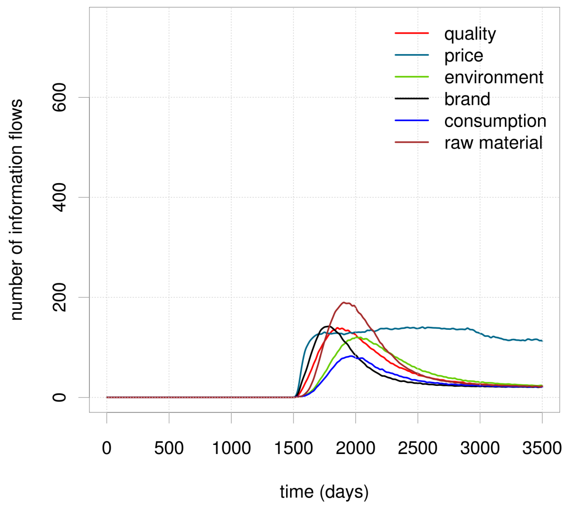
(a) Communication about unbranded conventional fuel



(b) Communication about branded conventional fuel

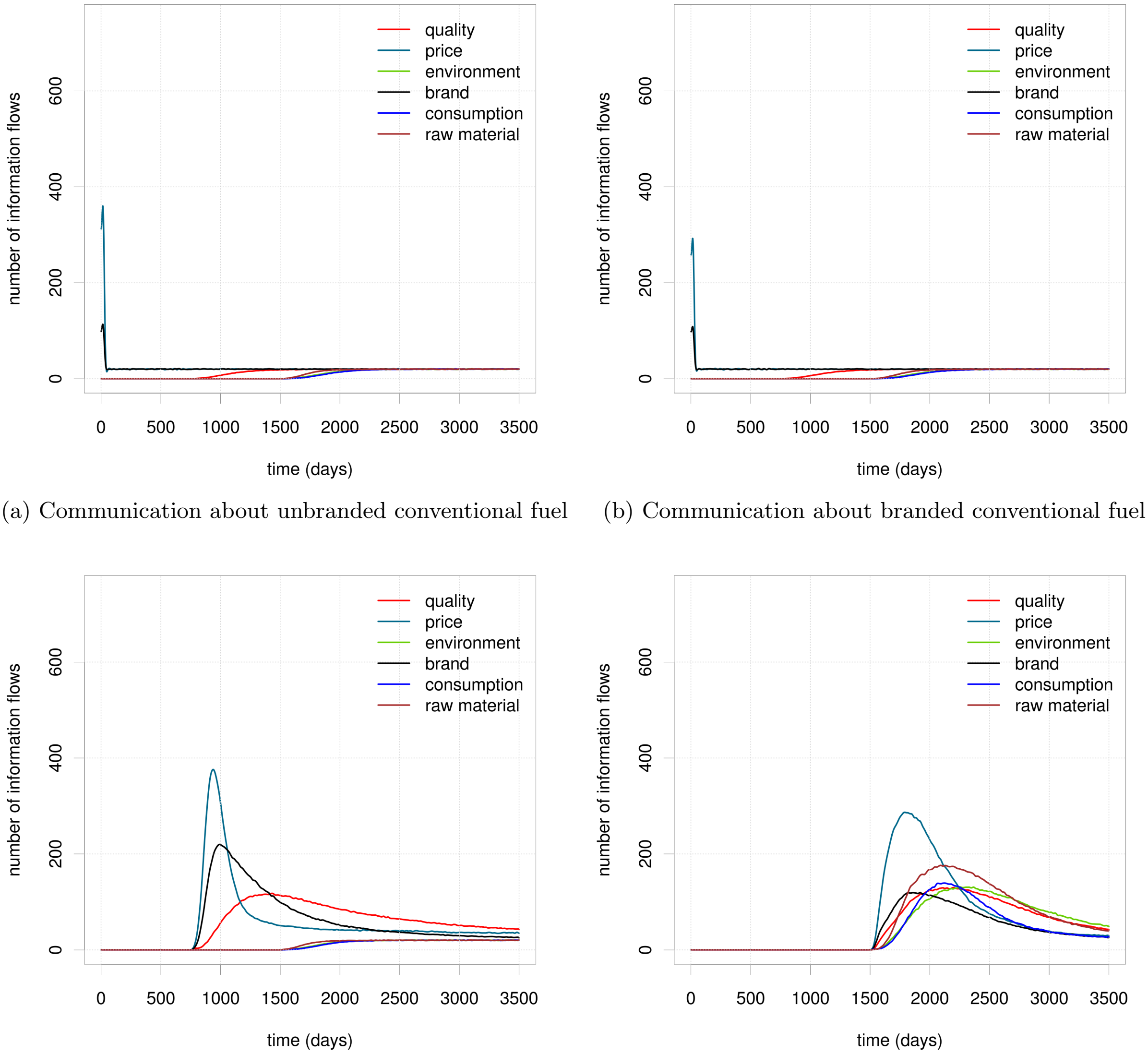


(c) Communication about premium fuel



(d) Communication about BtL-fuel

Figure A.3.: Number of communication events by attributes over time for $p_{BtL} = 1.2$ (5 consumer assignments to nodes x 10 random seeds = 50 replications)



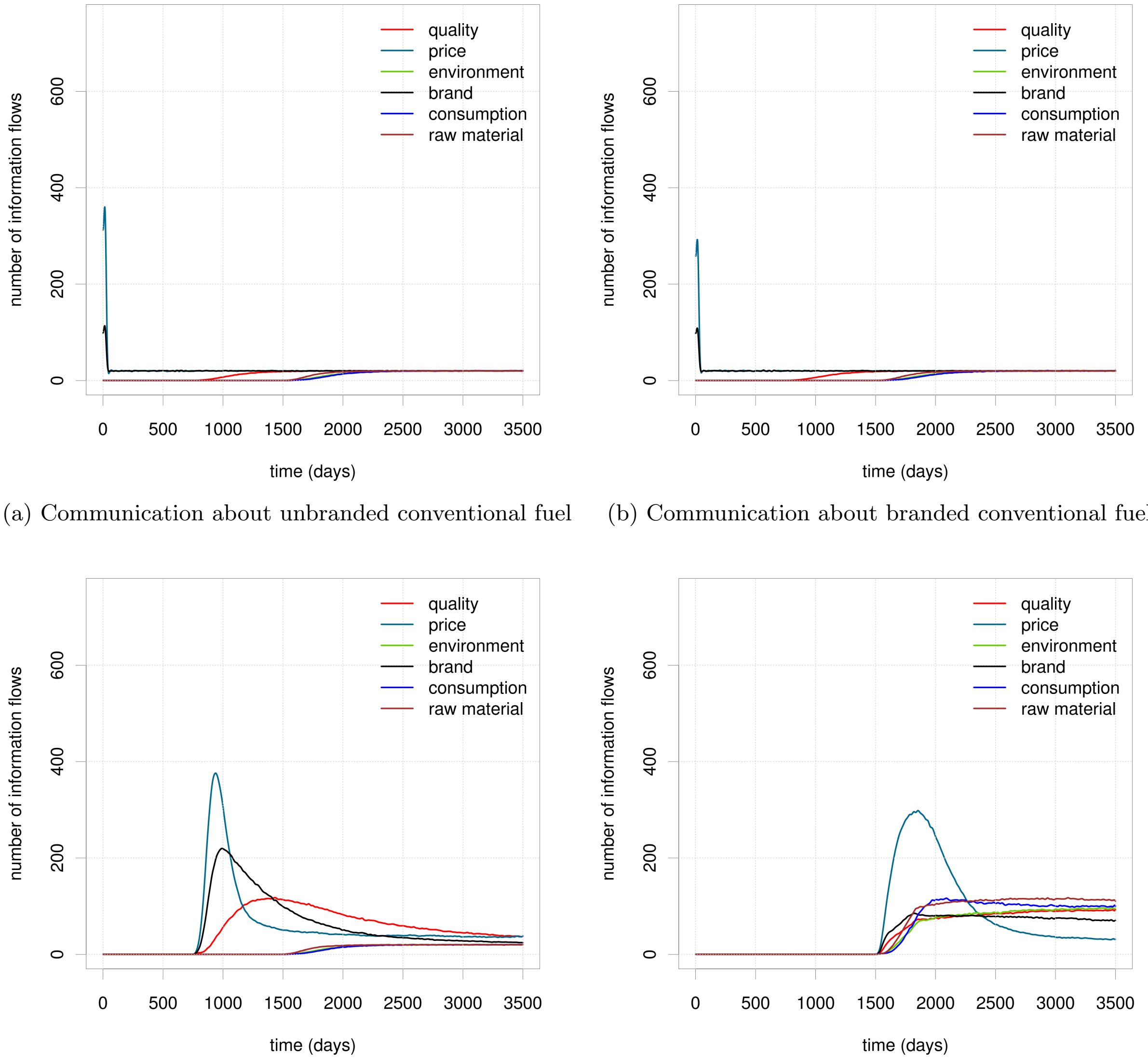
(a) Communication about unbranded conventional fuel

(b) Communication about branded conventional fuel

(c) Communication about premium fuel

(d) Communication about BtL-fuel

Figure A.4.: Number of communication events by attributes over time for $p_{BtL} = 1.3$ (5 consumer assignments to nodes x 10 random seeds = 50 replications)



(a) Communication about unbranded conventional fuel

(b) Communication about branded conventional fuel

(c) Communication about premium fuel

(d) Communication about BtL-fuel

Figure A.5.: Number of communication events by attributes over time for $p_{BtL} = 1.4$ (5 consumer assignments to nodes x 10 random seeds = 50 replications)

A.5. Theoretical network topology experiments

We compare networks with the same number of vertices ($|V| = 1{,}000$) and edges ($|E| = 2{,}000$), but varying topology, generated by the generative algorithms specified in Subsection 4.3.5 of this thesis. We create 10 network instances for each parameter setting and perform 50 replications, i.e., 500 runs per network parameter setting. To eliminate all factors other than the network structure, we use a scenario in which there is one superior innovation that is always adopted once an agent becomes aware of it and one "dummy" incumbent product. Only a single attribute and no price is used. The $n^{consumers} = 1,000$ agents are homogeneous in their preferences and communication events are scheduled according to a $Pois(30)$ distributed arrival process. The purchase interarrival time is fixed to 1. The algorithms compared as well as the number of parameter settings and replications are summarized in Table A.2.

Topology	Algorithm	Parameters and replications
Random	Gilbert (1959)	10 network instances x 50 reps.
Scale-free	Barabási and Albert (1999)	10 network instances x 50 reps.
Small-world	Watts and Strogatz (1998)	10 network instances x 50 reps. x 3 levels of randomness
Spatial clustering	Sen and Manna (2003)	10 network instances x 50 reps x 3 x 3 spatial/clustering levels

Table A.2.: Network algorithms and parameter settings compared in experiment

Random networks (Gilbert, 1959)

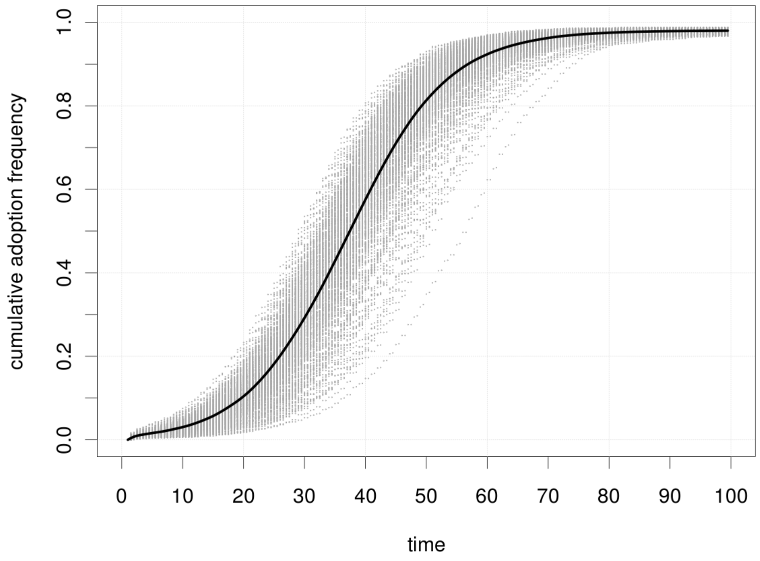


Figure A.6.: Diffusion in random networks (10 network instances x 50 replications)

Scale-free networks (Barabási and Albert, 1999)

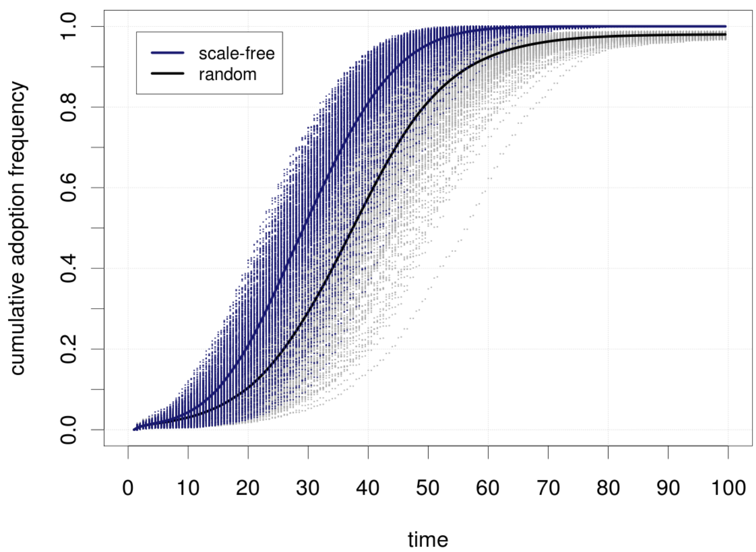


Figure A.7.: Diffusion in scale-free vs. random networks (10 network instances x 50 replications each)

Small-world networks (Watts and Strogatz, 1998)

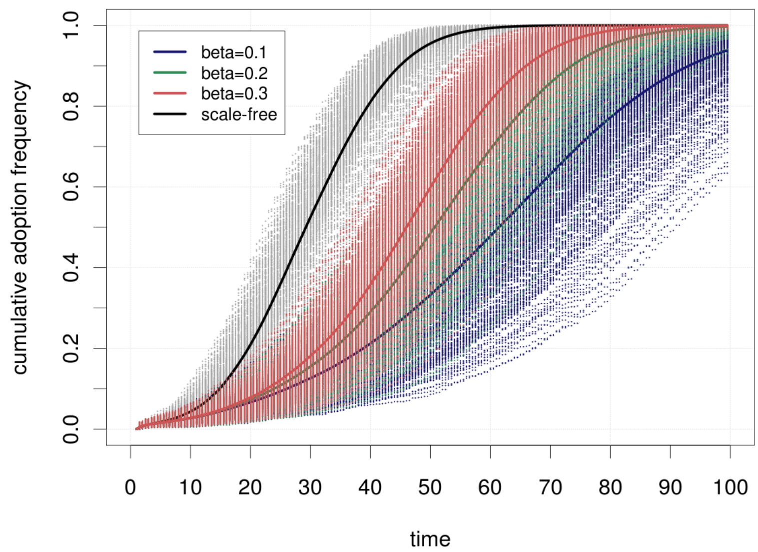


Figure A.8.: Diffusion in small world vs. scale-free networks (10 network instances x 50 replications)

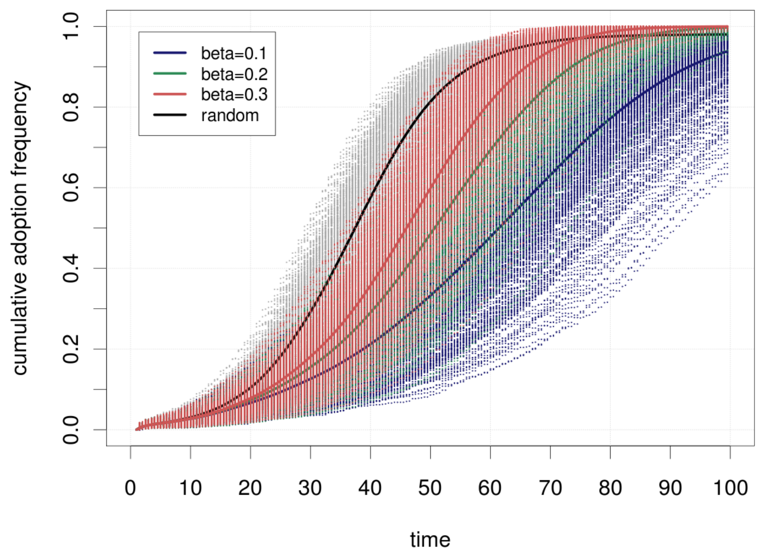


Figure A.9.: Diffusion in small world vs. random networks (10 network instances x 50 replications)

Spatial clustering networks

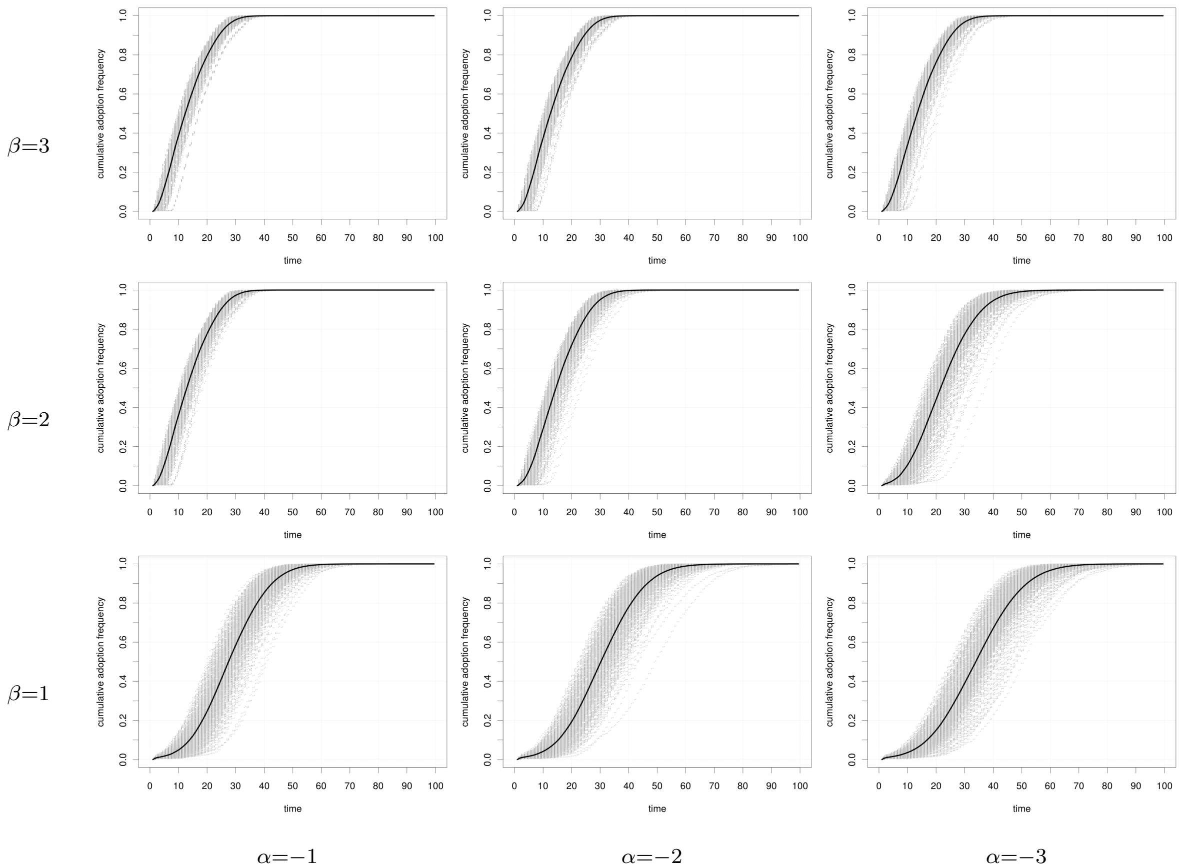


Figure A.10.: Diffusion in spatial clustering networks with random positioning for various values of α and β (10 network instances x 50 replications for each setting)

Comparison and Conclusions

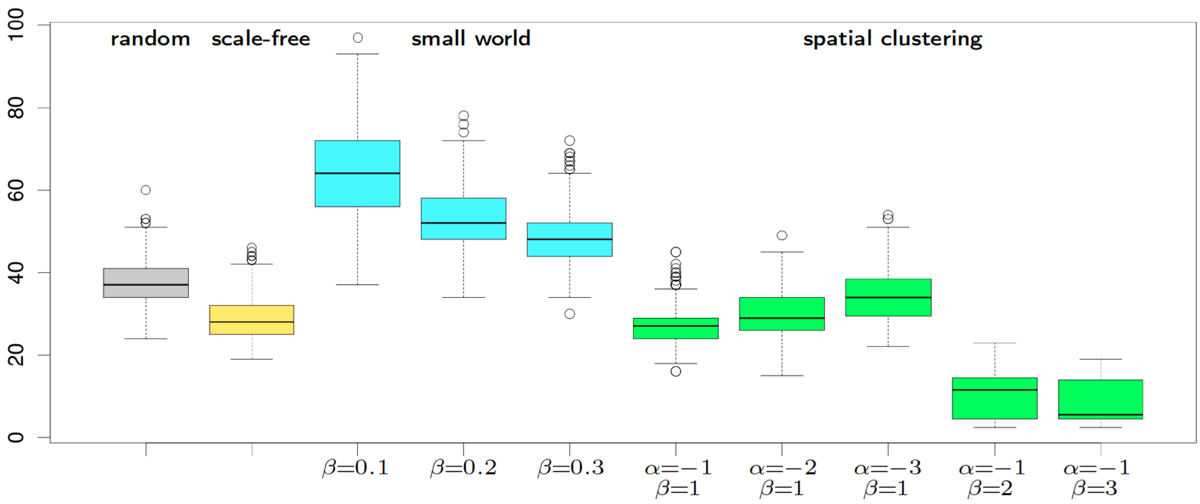


Figure A.11.: Peak times of adoption

Results are consistent with findings in the existing literature (cf. the review in Subsection 3.3.3). In particular, results indicate that when eliminating all influences other than the spread of awareness, diffusion is fastest in scale-free networks, followed by random and small-world networks. With respect to the spatial networks introduced in this thesis, which have not been investigated in any other diffusion study so far, results show that diffusion is generally fast in the parameter range considered, typically considerably faster than in small world networks. Another interesting finding is that a more localized social network structure leads to slower slower diffusion and in networks in which links are more global, diffusion occurs faster.

Planning the market introduction of new products: An agent-based simulation of innovation diffusion

Abstract

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Keywords
innovation diffusion; new product launch strategies; agent-based modeling and simulation; management decision support; multi-attribute consumer decision-making; repeat purchasing behavior; spatial diffusion; social network modeling; roll out; pricing strategy; second generation biofuels

In today's competitive business environment, firms' ability to create and maintain competitive advantage and secure long-term survival are critically dependent upon their ability to successful market innovations. Quantitative models of innovation diffusion have therefore attracted strong interest both from management scholars and from practitioners responsible for new product marketing decisions. Pioneering efforts to describe the diffusion of innovations mathematically were made in the 1960s. The aim of these models is to provide empirical generalizations of prototypical diffusion patterns at the aggregate (i.e., market) level in order to estimate the likely diffusion of a new product through extrapolation from early sales; to this end, they typically require considerable amounts of data covering most of the product's lifespan. Aggregate models cannot account for heterogeneity and social structure and are limited in their potential to evaluate likely effects of decision variables on the diffusion process.

The main objective of this thesis is to introduce a diffusion model that can support decision-makers in the process of planning the market introduction of new products. To this end, agent-based modeling and simulation, a methodological innovation that has increasingly been adopted in the social sciences in recent years, is applied to overcome inherent limitations of phenomenological aggregate-level approaches. This bottom-up approach conceives the diffusion of innovations as a complex social phenomenon that emerges from the aggregated individual behavior and the interactions between individuals. It opens up new research opportunities because it can easily incorporate micro-level drivers of adoption, bounded rationality, and imperfect information as well as individuals' heterogeneity in terms of attributes, preferences, behavior, and linkages in the social network.

This thesis identifies and aims at a research gap between purely abstract models of innovation diffusion aimed at general theoretical insights on the one hand, and highly specialized models tailored to a particular practical application on the other hand. The agent-based approach offers excellent opportunities to develop a generic and versatile model that can be applied to a wide range of specific problems. Furthermore, it allows us to pursue cutting-edge research interests including spatial diffusion, diffusion in a competitive context, product-level rather than industry-level analysis, and managerial diagnostics. In particular, the thesis contributes by (i) modeling all stages of the innovation-decision process, (ii) modeling sales rather than exclusively focusing on initial adoption, (iii) modeling the competitive diffusion of multiple products, (iv) complementing the temporal focus with the spatial dimension, (v) incorporating a spatially explicit social network model, and (vi) incorporating multi-attribute consumer decision-making.

The capability of the model to tackle real world problems is illustrated by means of a particularly interesting, empirically grounded application study on the diffusion of a second generation biofuel at the Austrian market. Various simulation scenarios demonstrate how the model can be used to plan the market introduction of this innovation. Findings suggest that while a competitive

price is unsurprisingly an important driver for adoption, there is a limited market potential for a high quality second generation biofuel at a higher price level than that of conventional fuels.

The simulation enables potential investors to assess the effectiveness of various approaches towards selecting gas stations for distribution while accounting for limited production capacity, availability of rich sources of biomass, and the geographic concentration of consumers. It also allows a decision-maker to evaluate the effectiveness of pricing strategies under varying assumptions about future energy market developments. The sample application illustrates how the agent-based model introduced in this thesis can provide managers with valuable decision support in the process of developing product launch strategies in a competitive setting.

Planning the market introduction of new products: An agent-based simulation of innovation diffusion

Abstract

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Schlüsselwörter
Diffusion von Innovationen; Agentenbasierte Modellierung und Simulation; Entscheidungsunterstützung; Markteinführungsstrategien; Räumliche Diffusion; Konsumentenverhalten; Multiattributmodell; Wiederkaufverhalten; Modellierung sozialer Netzwerke; Biokraftstoffe der zweiten Generation

In einem zunehmend dynamischen Wettbewerbsumfeld bildet die Fähigkeit zur erfolgreichen Vermarktung von neuen Produkten eine entscheidende Grundlage für den langfristigen Erfolg von Unternehmen. Quantitative Modelle der Verbreitung (Diffusion) von Innovationen in einem sozialen System sind daher sowohl für Wirtschaftswissenschaftler als auch für Manager, die Unterstützung bei der Entwicklung von Markteinführungsstrategien benötigen, von besonderem Interesse. Erste Modelle zur mathematischen Beschreibung von Diffusionsverläufen wurden bereits in den 1960er-Jahren entwickelt. Ziel dieser Modelle ist die empirische Generalisierung von typischen Diffusionsmustern auf aggregierter (d.h. Markt-) Ebene, um den wahrscheinlichen Verlauf der Adoption durch Konsumenten mittels Extrapolation aus frühen Verkaufszahlen abzuschätzen. Für zuverlässige Schätzungen benötigen diese Modelle allerdings Daten über den Großteil des Produktlebenszykluses. Überdies berücksichtigen aggregierte Modelle weder die Heterogenität von Konsumenten noch die Struktur ihrer sozialen Interaktionen. Schließlich eignen sich diese Modelle nur bedingt zur Erprobung des Einflusses von Marketing-Entscheidungsvariablen auf den Diffusionsverlauf.

Das Hauptziel dieser Dissertation ist die Entwicklung eines Diffusionsmodells das Entscheidungsträger bei der Planung einer Markteinführungsstrategie für neue Produkte unterstützen kann. Zu diesem Zweck wird agentenbasierte Modellierung und Simulation, eine Methode die in den letzten Jahren in den Sozialwissenschaften zunehmende Verbreitung gefunden hat, eingesetzt. Diese Methode begreift die Diffusion von Innovationen als komplexes emergentes Phänomen, das durch soziale Interaktionen und individuelle Adoptionsentscheidungen von heterogenen Individuen zustande kommt. Ein solcher Bottom-Up-Ansatz ermöglicht es, die prinzipbedingten Einschränkungen von aggregierten Ansätzen zu überwinden und eröffnet damit neue Forschungsmöglichkeiten. Insbesondere können Aspekte wie Adoptionsentscheidungsfaktoren auf Mikroebene, beschränkte Rationalität, unvollständige Information sowie die Heterogenität von Konsumenten hinsichtlich ihrer Präferenzen, ihres Verhaltens und ihrer Verbindungen im sozialen Netzwerk berücksichtigt werden.

Die Dissertation zeigt eine Forschungslücke zwischen abstrakten theoretischen Modellen einerseits und angewandten Modellen für bestimmte, sehr spezifische Einsatzbereiche andererseits auf und zielt darauf ab zur Schließung dieser Lücke beizutragen. Der agentenbasierte Ansatz bietet ausgezeichnete Möglichkeiten zur Entwicklung eines generischen und vielseitig einsetzbaren Modells das es erlaubt, aktuelle Forschungsinteressen wie etwa die Diffusion von Innovationen in einem kompetitivem Wettbewerbsumfeld, die räumliche Diffusion von Innovationen oder die Analyse auf Produktebene anstatt auf Branchenebene zu verfolgen. Insbesondere trägt die Dissertation durch (i) die Modellierung aller Stufen des Adoptionsentscheidungsprozesses, (ii) die Erfassung des gesamten Marktes anstatt der Beschränkung auf Erstadoptoren, (iii) die Modellierung der Diffusion einer Innovation in einem Markt mit mehreren Mitbewerbern, (iv) die Erweiterung der zeitlichen

Betrachtung von Diffusionsprozessen durch eine räumliche Dimension, (v) die Modellierung eines räumlich definierten sozialen Netzwerkes und (vi) die Einbeziehung von Konsumentenpräferenzen hinsichtlich mehrerer Produktattribute zur Diffusionsforschung bei.

Die Eignung des Modells zur Entscheidungsunterstützung in realen Problemstellungen wird anhand eines Anwendungsfalls zur Diffusion eines Biokraftstoffs der zweiten Generation auf dem österreichischen Markt illustriert. Anhand von Simulationsszenarien wird demonstriert, wie das Modell die Planung der Markteinführung einer solchen Innovation unterstützen kann. Ergebnisse zeigen, dass ein wettbewerbsfähiger Preis, wie erwartet, ein wichtiger Adoptionstreiber ist. Zudem weisen die Ergebnisse aber auch darauf hin, dass ein gewisses Marktpotential auch bei einem Preis oberhalb des Niveaus von konventionellen Kraftstoffen besteht. Die Simulation erlaubt potentiellen Investoren die Erprobung unterschiedlicher Strategien zur Auswahl von Vertriebsstellen unter Berücksichtigung von beschränkter Produktionskapazität, lokaler Verfügbarkeit von Rohstoffen und der geographischen Verteilung von Konsumenten. Außerdem ermöglicht es die Simulation, Preisstrategien unter unterschiedlichen Annahmen hinsichtlich zukünftiger Entwicklungen auf dem Rohölmarkt zu testen. Der Anwendungsfall zeigt damit, dass das entwickelte agentenbasierte Diffusionsmodell Entscheidungsträgern wertvolle Unterstützung bei der Entwicklung von Markteinführungsstrategien in einem kompetitiven Marktumfeld bietet.

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Current position

2010– *Researcher*, FWF research project
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Appointments held

2009 Researcher
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Research interests

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Education

2008– PhD Management, University of Vienna
2005 Studies at University of Oulu, Finland (Erasmus program)
2001– Business Informatics Master program at Vienna University of Technology
2000–2007 International Business Administration (Main subjects: International Management, Innovation and Technology Management, Master degree awarded with great distinction)

Publications

Journal Articles

2011 Kiesling E., Stummer C., Günther, M., Wakolbinger L. (2011), Agent-based simulation of innovation diffusion: A review. *Central European Journal of Operations Research*, forthcoming

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Peer-Reviewed Book Contributions

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Others

Booklet of Extended Abstracts for the *International Workshop on Agent-based Simulation of Diffusion Processes*, University of Vienna, ISBN 987-3-200-01835-8

Papers under review

2011 Gettinger J., Kiesling E., Stummer, C., Vetschera R. (2011), Problem representations for multi-criteria portfolio selection: An experimental comparison. Submitted to *Decision Support Systems*, Elsevier

Talks

2010 Kiesling E., "Agentenbasierte Simulation der Diffusion eines synthetischen Biotreibstoffes", iTIME series invited talk, University of Bielefeld, Germany, November 3, 2010.

Kiesling E., Günther M., Stummer C., Vetschera R., Wakolbinger L.M., Spatial social networks in an agent-based model of new product diffusion, *European Conference on Operational Research (EURO XXIV)*, Lisbon, Portugal, July 11-14, 2010.

Stummer C., Kiesling E., Gettinger J., Vetschera R., Using interactive heatmaps and parallel coordinate plots to support multi-criteria portfolio selections, *European Conference on Operational Research (EURO XXIV)*, Lisbon, Portugal, July 11-14, 2010.

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2008 Kiesling E., Günther M., Stummer C., "A business gaming simulation in innovation and technology management", *IFORS Conference*, Sandton, South Africa, July 13–18, 2008.

2007 Stummer C., Kiesling E., Gutjahr W.J., "Interactive decision support for competence-driven project selection in a research center", *INFORMS International Meeting*, Rio Grande, Puerto Rico, July 8–11, 2007.

2006 Günther M., Kiesling E., Stummer C., "Konzeption, Entwicklung und Einsatz eines Unternehmensplanspieles im Innovations- und Technologiemanagement", *Interactive Computer Aided Learning (ICL)*, Villach, Austria, Sept. 27–29, 2006.

Programs attended

2005 European Intensive Programme on Information Security Management and Technology Security (IPICS 2005), Sixth Winter School, Oulu, Finland, March 30–April 7, 2005.

Reviewing

2011 Central European Journal of Operations Research (CEJOR)
2010 International Journal of Innovation and Technology Management (IJITM),
Central European Journal of Operations Research (CEJOR)

Committees

2010 Organizing committee for the *International Workshop on Agent-based Simulation of Diffusion Processes*, Vienna, Austria, Apr. 8–9, 2010.

Research Project Proposals

Multi-Objective Support for Efficient Information Security Safeguard Selection (MOSES^3), (in cooperation with ao. Prof. Dr. Christine Strauss, Prof. Dr. Christian Stummer), approved by Austrian Science Fund in March 2011

Teaching Experience

Course	summer 2007	summer 2008	winter 2008	summer 2009	winter 2009	summer 2010	winter 2010	summer 2011
Management of innovation and technology, 4 ECTS course in Business Administration Bachelor program, University of Vienna		1	1	2	1	3	1	
Innovation management, 8 ECTS course in Business Informatics Master program, University of Vienna						1		1
Innovation Management, 3 ECTS course in Technical Sales and Distribution Management Bachelor program, University of applied sciences Bfi Vienna								1
Technology Management, 3 ECTS course in Technical Sales and Distribution Management Bachelor program, University of applied sciences Bfi Vienna								1
Operations Research in Production and Logistics, Tutor for 4 ECTS course in Business Administration Master program, University of Vienna	1							

Scientific memberships

Österreichische Gesellschaft für Operations Research (ÖGOR)
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Skills

Computer

Advanced programming skills (Java, C#, C/C++, Perl, PHP, R)
System administration (OS X, Linux, BSD, and Windows Systems)
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German (mother tongue)
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