

**Agent-based simulation of regulatory interventions to
promote the diffusion of Smart Metering in Germany**

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Martin Rixen

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Referee: Prof. Dr. Jürgen Weigand

Co-Referee: Prof. Dr. Markus Reisinger

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List of Abbreviations

a.k.a	Also known as
Const.	Constant
cum.	Cumulative
e.g.	exempli gratia; for example
EU	European Union
Fig.	Figure
in T	In thousands
KISS	Keep it simple, stupid
KPI	Key Performance Indicator
kWh	Kilowatthour
mDGP	Model Data Generation Process
No.	Number
p.	Page
RAM	Random Access Memory
rwDGP	Real-world Data Generation Process
Scen.	Scenario
SQL	Structured Query Language
UML	Universal Modeling Language
w/	With

1. Introduction

The diffusion of innovations has been an important field of research for decades, because product and process innovations are major sources for creative destruction (Banbury & Mitchell, 1995). In the last couple of years, widely-accepted explanatory frameworks—namely Epidemic and Probit diffusion models (Geroski, 2000)—were extended in the direction of *induced* diffusion. Induced diffusion of innovations tackles aspects how e.g. regulators intervene into the diffusion procedure in order to artificially boost adoption-speed and adoption-level (Diaz-Rainey, 2009). Concern in this research area developed due to recent inducements of ‘Green’ innovations: Climate protection initiatives and CO₂ abatement goals require fast and widespread diffusion of e.g. organic fuel E10, photovoltaic, electric vehicles, and combined heat and power. ‘Green’ innovations are typically disruptive and may cause competitive advantages for economies (Christensen, 2000; Christensen, Suárez, & Utterback, 1998). But design of effective and efficient inducements is difficult. Wrong decision making may cause non-adoption and/or uncontrollable costs.

One important ‘Green’ innovation is *Smart Metering*. Smart Meters allow frequent measurement processes within energy supply infrastructure enabled by Information- and Communication-Technology. E.g. in terms of electricity, Smart Meters will replace conventional *Ferraris* meters. Other applications are gas and water supply. Smart Metering is a major prerequisite to evolve the conventional energy grids into sustainable *Smart Grids* (Brophy Haney, Jamasb, & Pollitt, 2009; Kester, Burgos, & Parsons, 2009). These grids enable load-dependent feed-ins of decentralized energy sources like photovoltaic and plug-in (hybrid) electric vehicle batteries as well as large-scale power plants like offshore wind-farms and *Desertec* (World Economic Forum, 2009).

Diffusion strategies for Smart Metering differ geographically and depend on environmental, technological, regulatory, and cultural drivers. Adoption results range from almost zero (e.g. Germany) to nationwide deployments (e.g. Italy). A variety of countries induce the diffusion through monetary grants, informational interventions, and state-aided large-scale pilot projects, e.g. the United States, Australia, and China. Other countries liberalized the metering market in order to promote competition and consumer demand for Smart Metering tariffs. Especially Germany, the Netherlands, and Great Britain try to induce adoption through liberalization. These three countries are comparable regarding their liberalized energy markets (Pollitt, 2009) and face similar obstacles in the inducement of Smart Metering diffusion (Vasconcelos, 2008). Finally, diffusion proceeds too

slowly in these three countries and jeopardizes the fulfilment of the European Directive of 80% spatial diffusion until 2020 (European Parliament, 2006).

Objective of this doctoral thesis is to compile, predict, and evaluate policy options to induce the diffusion of Smart Metering with a focus on the German market. Results contribute to the discussion, how Germany's regulator *Bundesnetzagentur* can shape new regulatory frameworks in order to tackle adoption barriers and induce diffusion. From a methodical perspective, network effects (Rogers, 1976) as well as adopter heterogeneity (Herbert, 2006; Rogers, 2003) are critical requirements for a model that simulates innovation diffusion. Agent-based models are well-suited to handle the complexity of both requirements (Gordon, 2003; Rahmandad & Sterman, 2008). These capabilities are critical factors within innovation diffusion research and make Agent-based modeling a promising venue for developing new diffusion theory (Macy & Willer, 2002; Rand & Rust, 2011; Zenobia, Weber, & Daim, 2009). In order to derive regulatory recommendations, we develop a feasible methodology based on maturity requirements in Chapter 2. Then, design and build of a corresponding Agent-based model to simulate policy induced diffusion of innovations follows in Chapter 3. Finally, methodology and model are applied to the German Smart Metering market in Chapter 4. All three Chapters 2, 3 and 4 contribute to literature and were submitted to scientific Journals as exclusive Essays.

Chapter 2 contains a methodical Essay, focusing on empirical validation techniques in the context of Agent-based modeling. It establishes fundamental requirements for the predictive models in Chapter 3 and 4. Validity is crucial to evolve simulation 'toys' into useful research 'tools' in order to enable the prediction of policies. A holistic maturity matrix that aggregates common empirical validation taxonomies is developed and applied to an innovation diffusion example. Results will show that in terms of validation, one size does not fit all purposes. The best-suited validation approach depends on the model's objective and the availability of data.

Chapter 3 develops an endogenous supply-demand model to simulate innovation diffusion. Empirical validation is approached based on the findings from Chapter 2. The model includes both major diffusion concepts (*Epidemic* and *Probit*) and allows scenario-based simulation of inducements. Three inducements are tested in the model: Market liberalization, information policies, and monetary grants. Adoption forecasts are analyzed in terms of effectiveness (speed and level) and efficiency (costs and welfare) in order to evaluate chances and risks of each intervention scenario. A set of ten propositions concludes the findings.

Chapter 4 picks-up validity-, model-, and policy-related findings from Chapter 2 and 3 in order to map the German Smart Metering market. Special focus is on consumer demand processes to locate demand-side barriers and drivers. Findings highlight weaknesses in current regulatory

requirements due to disadvantages in consumer acceptance and policy effectiveness. A ‘cash-for-clunkers’-program is discussed to tackle major barriers for adoption and boost diffusion through synergies of pricing and promotion interventions.

Overall concluding remarks as well as future research directions based on the most important findings are presented in Chapter 5.

2. Maturity Levels in Empirical Validation¹

2.1 Abstract

Diverse empirical validation taxonomies have been published in the context of Agent-based modeling. Validity is crucial to evolve garbage-in/garbage-out ‘toys’ into useful research ‘tools’. But the amount of taxonomies as well as methodical discrepancies confuses academia and slows down its circulation in literature. We tackle these obstacles in this study. We explain, compare, and apply popular validation techniques and aggregate them into a holistic framework: The maturity matrix. It covers nine maturity levels, ranging from simple grounding to complex input-output calibration. Stepwise validation of an exemplary innovation diffusion model showcases each maturity level applied. We conclude our findings in six propositions. Basically, the best-suited validation approach depends on the model’s objective and the availability of data. One size does not fit all. Explanatory models may reduce validation effort by using statistical approximations, while predictive models rely on accurate parameter-matching. We explain microdata calibration in detail. It is rarely discussed in literature but leads to highest validity. Benefits particularly exist in computational economics due to the availability of data. A combined use of microdata and Data Mining enables modelers to keep models simple, without losing the ability to analyze complex output time-series.

2.2 Introduction

Agent-based models are simple reconstructions of complex real-world systems (Moss, 2001). They simulate decision-making entities that perform behavior rules in a virtual environment (Bonabeau, 2002). As a research methodology, it has been established in different research areas during the past 20 years (Heath, Hill, & Ciarallo, 2009). Research contribution originates from emergent and immergent effects (Edmonds, 2010) as well as from behavioral and structural target system analyses (Zeigler, Praehofer, & Kim, 2005). Key capability is the handling of numerous input factors to reconstruct complex systems and complex behavior (Edmonds, 2001b). This opens a broad range of applications, as *Epstein* (2008) concludes: Prediction is most important, others are explanation and education.²

¹ Rixen, M. & Weigand, J. (2012). Maturity Levels in Empirical Validation. Unpublished manuscript.

² See <http://ccl.northwestern.edu/netlogo/models> for various examples. These models can be executed online in the browser without installation. Further models can be downloaded from <http://www.openabm.org/models>.

Handling of complexity is a key strength, but also a major source for errors and critique. Complexity inflates the model and leads to over-parameterization: First, due to a high number of variables. Second, because of assumptions and randomizations in the configuration among these variables. Both aspects decrease replicability and significance of Agent-based models (Axelrod, 1997; Galán et al., 2009; Leombruni & Richiardi, 2005). To address increasing number of variables, academia adopted the keep-it-simple principle of *Axelrod* (2003). Models that base on simple rules and few configuration parameters are superior regarding interpretation and replication (Batten, 2000). They do not necessarily produce simple results. In contrast, simple predictors frequently result in complex behavior, if they are executed in a multi Agent environment. But how strong do stylized attributes correlate with real-world characteristics? Is real-world behavior of individuals as rational and simple as in the artificial world? How lifelike are simulation assumptions, behavior, and estimations?

Empirical validation addresses these questions. It reduces discrepancies between model and target system and is critical for the model's significance. Empirical validation avoids stupid garbage-in/garbage-out simulations based on assumptions and randomizations. Even numerous parameters could be used in a complex model, as long as these parameters are validated with real-world data. Empirical validation is a frequent subject and hot topic in the scientific community. A variety of techniques have been published (a comprehensive review follows in section 2.3). Nevertheless, these techniques differ in...

- scope (e.g. direct input calibration vs. indirect output validation),
- granularity (e.g. use of aggregated time-series vs. empirical microdata),
- accuracy (e.g. anecdotic knowledge vs. empirical data),
- effort (e.g. simple random distribution vs. complex matching of variables),
- naming (input/output validation, direct/indirect calibration, internal/external validation etc.).

Objective of this paper is to review popular validation techniques, identify gaps and similarities, and develop a holistic framework to clarify the above conflicts. Our framework is structured in maturity levels to enable validity evaluations. For instance, validation based on stylized facts results in low maturity, while direct calibration with high-granular microdata means high maturity. Although microdata calibration leads to superior maturity, it has been rarely discussed in literature. We extend current research with detailed explanations on this validation technique. Its application is difficult and requires several data preparation steps, but availability of data in the form of Scientific-Use-Files and Public-Use-Files makes microdata calibration a promising venue in Agent-based computational economics.

We apply our maturity framework stepwise to an innovation diffusion model in *NetLogo*. The Agent-based paradigm is well suited in the innovation diffusion context. Core capabilities enable network effects and Agent heterogeneity, mapping both primary innovation adoption drivers: *Epidemic* learning and attainment of *Probit* thresholds (Geroski, 2000). Published models typically focus on one of both drivers. Our model includes both drivers with co-evolutionary supply-and-demand through awareness-spread, supplier entry/exit, and Cournot competition.

The following literature review outlines published validation taxonomies. We re-use these taxonomies to describe the development of our maturity matrix in section 2.4. Detailed explanations on microdata calibration follow in section 2.5. Section 2.6 applies the maturity levels to an innovation diffusion example. We discuss and conclude our findings regarding empirical validation, maturity levels, and its application to specific purposes within six propositions in sections 2.7 and 2.8.

2.3 Literature Review

Agent-based models are simple reconstructions of complex real-world systems (Moss, 2001). They simulate decision-making entities that perform behavior rules in a virtual environment (Bonabeau, 2002). *Galán et al.* (2009) present four modeling stages to reconstruct the real-world in an executable computer program: Abstraction, design, approximation, and coding. Each of the four stages includes specifications to proceed from the target system to a replicable model. Replicability is the ability to re-produce and re-execute a model in different frameworks (Wilensky & Rand, 2007). *Grimm et al.* (2005) developed the idea of *Pattern Oriented Modeling* to perform the four modeling stages for highly complex ecological models, that challenge modelers through over-parameterization. In line with common software development methodologies, specifications transform real-world observations into functional requirements and finally into executable code. Deviations in any of these specifications lead to deviations in the final program and therefore in simulation results. *Validation* is performed in order to avoid or reduce these deviations.

A valid Agent-based model is well-founded and corresponds accurately to the real-world.³ Validity is a two-dimensional requirement in the modeling context: *Carley* (1996) distinguishes between internal and external validity. *Internal* validity focuses on the correctness of the programming code. Internal validation ensures a correct implementation of functional requirements into computer code (technical design). In literature, it is often referred to as *verification* to describe how well the implemented model corresponds to the conceptual model (Rand & Rust, 2011). Vice

³ See [http://en.wikipedia.org/wiki/Validity_\(statistics\)](http://en.wikipedia.org/wiki/Validity_(statistics)) for definitions and an overview of different terms in the context of statistical validity.

versa, *external* validation tackles deviations of model configurations with real-world observations (Carley, 1996). It focuses on the validity of parameter calibrations, world conditions, and behavioral rules in coherence to the ‘external world’. Empirical data is leveraged for external validation. It is a frequent topic in simulation literature and main scope of this paper. From now on, any reference to validation/validity means *external* validation/validity.

Different approaches on empirical validation are mentioned in the literature. *Fagiolo, Moneta, and Windrum* (2007) compare three different taxonomies: The *indirect calibration*, the *Werker-Brenner*, and the *history-friendly* approach. They differ primarily in the type of utilized data and in validation procedures. *Indirect calibration* is performed in an iterative approach, focusing on *ex-post* comparison cycles of model outcomes with real-world data. The *ex-ante Werker-Brenner* approach includes the use of historical knowledge, while the *history-friendly* approach adds casual and anecdotic knowledge.

Carley (1996) distinguishes between four validation methods: *Grounding*, *calibrating*, *verifying*, and *harmonizing*. *Grounding* is a basic approach to match expectations with general model results. For example, a technology diffusion simulation is grounded if adoption time-series show the typical ‘S’-shape curve as discussed in the widely accepted *General Bass Model*. *Calibrating* is similar to the above mentioned *indirect calibration* approach: Initial conditions and rules are fine-tuned in iterative cycles unless outcomes match real-world observations. *Verifying* extends *calibrating* to predictive outcomes of the model, where availability of empirical statistics is limited. Finally, *harmonization* includes all three approaches plus comparisons of simulation outcomes with results from differential equation calculations.

Tesfatsion (2010) promotes a distinction between *descriptive output validation*, *prescriptive output validation*, and *input validation*. *Descriptive output validation* matches available real-world data with model outcomes. *Prescriptive output validation* utilizes the same process but different data: *Yet-to-be-acquired* real-world data is required. *Input validation* utilizes available empirical statistics to calibrate initial conditions in the Agent-based model.

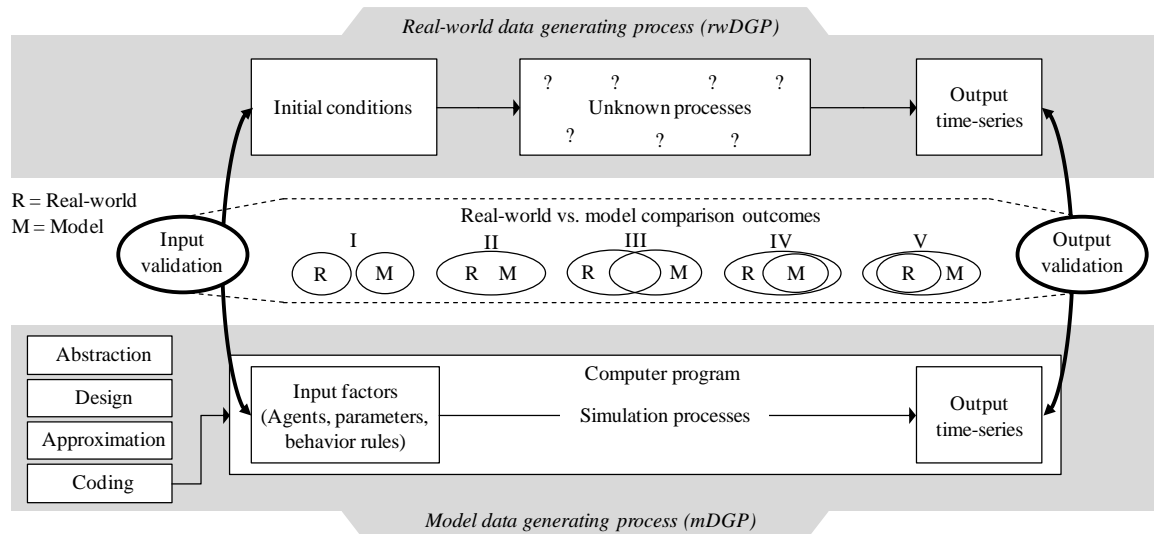


Fig. 1. Data generation and validation procedures (Fagiolo et al., 2007; Galán et al., 2009; Marks, 2007; Tesfatsion, 2010)

Fig. 1 summarizes a variety of important publications on validation in Agent-based modeling. It recaps the four modeling stages of Galán et al. (2009) and extends them with the comparison of data generating processes of Fagiolo et al. (2007): The real-world data generating process (rwDGP) and the model data generating process (mDGP). The mDGP tries to map the rwDGP, e.g. in order to explain it or predict future developments. The figure visualizes the idea of validation in the middle of both procedures. We distinct two different *validation-scopes* and adopt the terms *input validation* and *output validation* of Tesfatsion (2010) to describe them. Input validation focuses on the input factors (Agent characteristics, environmental parameters, and behavior rules), while output validation compares the model's output time-series with empirically measured real-world time-series. As Marks (2007) summarizes, these input and output comparisons may result in five different states (see Table 1 combined with the visualization in the center of Fig. 1):

Table 1. Comparisons and comparison outcomes (Marks, 2007)

No.	Condition	Evaluation
I	No intersection between R and M	The model is useless.
II	R is equivalent to M ($M \Leftrightarrow R$)	The model is complete and accurate.
III	Intersection is not null	The model is useful, to some degree. Yet it is both incomplete and inaccurate.
IV	M is a proper subset of R ($M \subset R$)	All the model's behaviors are correct (match historical behaviors). It is accurate but incomplete.
V	R is a subset of M ($R \subset M$)	All historical behavior plus some additional behaviors were exhibited. The model is complete but inaccurate.

The modeler's ultimate goal is state II, where model and real-world are equivalent. A few Agent-based models—e.g. in energy market simulations—come close to this state, as they reach an accurate match of input parameters and output time-series. States III, IV, and V normally occur. Distinctions in *validation-scale* drive the outcome: Small-scale validation picks only a few parameters and/or empirically validates with low granular data. Large-scale validation tries to compare as many parameters as possible with high granularity. Maximum granularity can be reached with the use of empirical microdata, technical specifications, and geographical coordinates.

We conclude this literature review with an example of the famous *Sugarscape* model by *Epstein and Axtell* (1996).⁴ The model explains wealth distribution. Input factors are defined by parameters that characterize the environment (number of Agents, distribution of sugar, etc.) as well as Agent heterogeneity (metabolism rate, maximum age, etc.). Behavioral rules determine the Agent's search for places with additional sugar and their movement to this better position. Input validation would compare these input factors with initial conditions and behavior in the real-world. Key performance indicators (KPIs) track periodic changes and accumulate them to output time-series, e.g. the distribution of wealth among Agents. Output validation would compare these time-series with empirical data and iteratively re-calibrate the mDGP, until model output matches real-world output.

2.4 Maturity matrix for empirical validation

2.4.1 Development of the maturity matrix

The review of validation techniques presented no dominant approach that fits for all models. Modelers select diverse taxonomies, driven mainly by the model's objective and availability of empirical data. The variety of different approaches delays the acceptance of Agent-based modeling among academia and complicates its circulation in scientific literature. Journal reviewers and readers who are unfamiliar with the Agent-based methodology can hardly follow each validation approach and evaluate the validity of parameters and Agent behavior.

This paper tackles the confusing variety of taxonomies. Our objective is the development of a holistic maturity framework that re-uses existing methods and categorizes them according to key drivers that influence decisions for specific methods. A holistic framework will help to identify 'white spots' that have not been discussed in literature and will create a common vocabulary. It will allow comparisons of published techniques to show their similarities and discrepancies. It will support modelers to choose the best-suited technique. Finally, the maturity matrix will help

⁴ See <http://sugarscape.sourceforge.net> or <http://ccl.northwestern.edu/netlogo/models/SugarscapeImmediateGrowback> for examples.

reviewers and readers to evaluate the validity of published models and compare them to their expectations.

We already identified two vital maturity dimensions in our literature review that differentiate common validation taxonomies: *Validation-scope* and *validation-scale*. *Validation-scope* tackles the point of comparison to real-world data. Two foundational directions exist (see Fig. 1): Input validation and output validation. The *Werker-Brenner* approach and Tesfatsion's *input validation* methods belong to the first category. The *indirect calibration*, *Carley's calibrating*, and *Tesfatsion's output validation* belong to the second category and determine an *ex-post* approach. The second maturity dimension that was derived from literature is *validation-scale*. It includes the magnitude and the granularity that is applied during validation. We use a straightforward distinction and categorize between small-scale and large-scale validation methods. Small-scale approaches validate only a subset of parameters with the use of low granular data (e.g. casual and anecdotic knowledge or statistical approximations). *Carley's grounding* and the *history-friendly* approach belong to this category. Large-scale approaches validate most or all parameters and apply high-granular data (e.g. empirical microdata).

Output validation	Large-scale	M-2 Indirect calibration	M-5 Approximation + Indirect calibration	M-8 Matching
	Small-scale	M-1 Grounding	M-4 Approximation + Grounding	M-7 Direct calibration + Grounding
	No validation	M-0 No validation	M-3 Approximation	M-6 Direct calibration
		No validation	Small-scale	Large-scale
		Input validation		

Fig. 2. Maturity matrix for empirical validation in Agent-based modeling

Nine levels divide validation-scope and validation-scale into a strict maturity ranking (see Fig. 2). These levels range from M-0 (no validation) to M-8 (matching). Its two-dimensional structure (scope and scale) aligns with common validation practices and was arranged based on the following orders:

- *Validation-scope > Validation-scale*: Scope is the primary dimension. Scale is secondary. The reason that makes scope the dominant dimension is the fact that scope is driven by the model’s overall objectives and therefore constitute a fundamental direction. Contrariwise, scale is usually determined by availability of data and the effort a modeler is willing to invest into validation. Scope keeps static, while scale is more flexible and may change during the modeling process.
- *Input validation > Output validation*: Input validation leads to higher maturity than output validation. Input is advantageous, because parameters and behavior are *directly* calibrated. Output validation calibrates input factors *indirectly* in an iterative manner, until output time-series match empirical outcomes. It leaves more room for errors and deviations. Difficulties incline with increasing numbers of parameters: Which parameter needs to be adjusted, if output time-series differ?
- *Small-scale validation > No validation*: Any validation is advantageous. Non-validated parameters and assumed behavior decrease explanatory power and allows misinterpretation. Even configurations upon anecdotic knowledge (e.g. the expectation that variable x must be greater than variable y) increases maturity.
- *Large-scale validation > Small-scale validation*: Large-scale validation is superior because it leaves less room for errors and deviations. The nature of bottom-up emergent effects causes even small deviations to accumulate to varying results on a macro level.

Naming conventions for the maturity matrix were partly adopted from literature. We adopted *Carley’s grounding* as well as the *direct/indirect calibration* naming conventions. We introduced *approximation* to describe small-scale input validation practices of models that use random distributions to approximate model and real-world conditions. We introduced *matching* to describe the highest maturity level. We adopted the term from computer science in the context of Data Quality: Matching is performed to compare any available data field (highest granularity level) with each other, primarily to identify and cleanse duplicates. Similar objectives apply to maturity level M-8 since as many variables as possible are validated to mirror the real-world inside a virtual duplication.

2.4.2 Validation-scope details

Input and output validation differ entirely in their practical approach. Input validation is a bottom-up approach that directly calibrates input factors. Vice versa, output validation modifies the same input factors, but indirectly from top-down. Aggregated model output (top) triggers adjustments of input factors (down). Iterative adjustments are beneficial due to the deep knowledge a modeler gains from trial-and-error activities. Root-causes, emergent effects, and basic sensitivities are routinely discovered. However, modelers are free to decide which parameter they want to adjust. They are able to adjust parameters until simulations result in the way they want it to. This bias is problematic in terms of maturity and makes output validation a less feasible option for predictive purposes. Input validation leads to smaller biases and reduces the modeler's freedom to influence model behavior. It leaves less space for (mis-) interpretation and assumptions.

Modelers are not flexible in choosing their validation-scope. Model objectives and availability of empirical data determine the selection. In terms of *model objectives*, we distinct between two fundamental directions:

- *Prediction*: Predictive models rely on input validation. Detailed output time-series are their primary research contribution, which leads to conflicts if these time-series were accurately calibrated *a priori* during output validation. Additionally, yet-to-be-acquired empirical data in line with *Tesfatsion's* (2010) prescriptive output validation taxonomy would be necessary. We will follow-up on these aspects in section 2.7, where we will discuss best-suited maturity levels per model objective. One special predictive configuration exists, in which large-scale output validation is necessary (baseline in scenario analyses).
- *Explanation*: Explanatory models map target system procedures in order to educate about general observations (e.g. occurrences of traffic jams) or specific research issues (e.g. heterogeneity impacts in innovation adoption). It is critical that the output is similar to real-world observations. Therefore, output validation is well-suited for explanatory models.

Availability of data determines the scope-selection as well. In principle, all input factors in Agent-based models can be directly validated with empirical data: Agent characteristics (e.g. income based on census data), behavior rules (e.g. purchase behavior based on price-dependent purchase probabilities), and environmental conditions (e.g. local dispersion based on geographical data). But published models confirm that validation of behavior rules and environmental conditions is challenging. They are usually simplified and contain assumptions. E.g. a fixed number of Agents populates a chessboard-like world and interact with bordering Agents. This setup is frequently used across academia, but it is rarely directly calibrated. *Grimm et al.* (2005) discuss the idea of *Pattern Oriented Modeling* in this context. Availability of empirical microdata in the form of Public-Use-

Files and Scientific-Use-Files enable highly-validated input conditions in the context of Agent-based computational economics.

A combined application of input *and* output validation combines benefits from both taxonomies and is advantageous through checks and balances. Checks and balances originate from the principle that both input and output validation tackle the same input factors. The output validation can be checked against input validation results and vice versa. Furthermore, parameters that have already been validated through direct input calibration, narrow down the list of parameters that need to be adjusted during output validation iterations. Two major obstacles exist: First, input and output validation may result in conflicts and leaves the modeler with the decision which configuration is valid. Nevertheless, these conflicts may end up in research contribution. Second, the validation effort may incline exponentially, because both techniques tackle the same parameters and any re-adjustment jeopardizes already finalized validations. E.g. an adjustment of a single (directly calibrated) parameter makes former output validations useless, since new output time-series mismatch the old time-series. We will apply a special sequence in our stepwise example in section 2.6 to explain how efforts can be limited (direct calibration first, followed by indirect output validation).

2.4.3 Validation-scale details

Scale is our second maturity dimension. We distinguish between three states: No validation, small-scale, and large-scale. Validation magnitude and granularity are primary drivers. *Magnitude* relates to the number of validated input factors. *Granularity* evaluates the level of detail of the applied empirical data. The following refinements explain each state in detail:

- *No validation*: Related models contain only non-validated parameters and behavior. Not even anecdotic knowledge is used. Models in this category are rare and mostly used for educational purposes, e.g. in tutorials that explain a modeling software and its functionalities.
- *Small-scale*: Related models calibrate with the use of random distribution. These approximations are frequently used in Agent-based simulations (Wilensky, 2010). The modeler's intention is to validate *efficiently*, with low effort but acceptable validity.
- *Large-scale*: Related models match real-world conditions as accurate as possible. Maximum *effectiveness* with minimum space for deviations is the modeler's intention. High-granular data is applied. If possible, validation includes *all* Agent characteristics, world conditions, and behavior rules. Missing empirical data is substituted by sensitivity analyses to avoid assumptions and approximations. Large-scale validation burdens modelers with high validation effort.

An alignment of validation-scale with model expectations is crucial. Deterrent examples exist especially in the context of predictive models, which try to predict time-series although their parameters are not validated or only small-scale validated. Missed expectations will jeopardize the acceptance of Agent-based modeling. Fig. 3 visualizes the three states on the scale-axis of the maturity matrix. Our three graphs and four examples (income calibration) should guide modelers to evaluate their model's validity requirements. The maturity matrix distinguishes between taxonomies that utilize microdata (raw or aggregated) and taxonomies that use randomized distributions. Models which base upon large-scale validation are superior in maturity. Nevertheless, their outcomes and the significance of produced results do not necessarily differ. E.g. microdata calibration and statistical approximations will result in equal outcomes, if real-world data is normally distributed. In this case, modelers can calculate arithmetic means and standard deviations from empirical data and approximate with high validity.

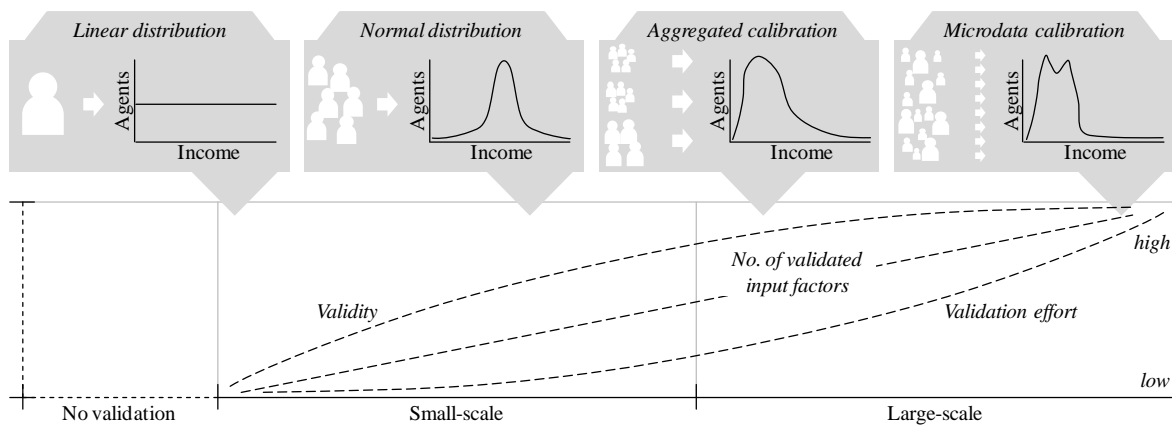


Fig. 3. Scale-axis of the maturity matrix with four input calibration examples

The trade-off between validation effort and level of validity leads to a non-trivial selection of the best-suited validation approach. As in the context of validation-scope, the taxonomy selection is driven by the experiment's objectives and the available empirical data. In the context of predictive modeling, high granularity and broad magnitudes are important. Empirical microdata is directly applied or aggregated into intervals to validate as many input factors as possible. Vice versa, explanatory models may reduce validation effort. E.g. the *Sugarscape* model utilizes random distribution of parameters to produce explanatory results. The number of validated parameters is usually limited due to the availability of data. While granularity is manageable, missing real-world data challenges modelers with the question: Why is the corresponding variable, that cannot be

validated, important? Non-validated and unimportant parameters should be removed or replaced in line with the keep-it-simple principle.

Large-scale validation burdens modelers with high validation effort. Depending on the model, it may massively increase the requirement for computational power. Especially output validation is impossible without the support of huge computational power that allows thousands of iterations in sensitivity analyses. The number of iterations rises exponentially with the number of input factors. Furthermore, output time-series typically include contingency effects due to random Agent selection, random dispersion, and other iteratively varying parameters. Various iterations per model configuration are necessary to factor-out these effects. Section 2.7 will follow-up on this aspect with calculation examples.

2.5 Microdata calibration

Although microdata calibration leads to highest maturity levels, it is rarely discussed in the literature. Different obstacles prevent researchers to take huge validation efforts into account. They would need to drill-down to high-granular records and integrate them into their models. This section extends current research and defines microdata, discusses advantages and limitations of microdata calibration, and explains procedures to integrate microdata into Agent-based models.

Microdata contain high-granular empirical study results with the highest level of detail: Non-aggregated records, e.g. survey answers of individual respondents. A suitable definition especially for census microdata was published by the *Minnesota Population Center*. It defines microdata as a composition “[...] of individual records containing information collected on persons and households. The unit of observation is the individual. The responses [...] are recorded in separate variables. [...] Microdata are inherently flexible. One need not depend on published statistics [...]. Users can generate their own statistics from the data in any manner desired, including individual-level multivariate analyses.” (Minnesota Population Center, 2010). In terms of microdata validation and in line with the above definition, we understand microdata as empirical outcomes with information stored on a single record level without aggregation. The one-to-one relationship to the unit of interest is crucial, e.g. relations to individuals, households, or companies. Publication of microdata is popular in the context of census surveys. Other examples are transportation statistics and driving patterns, political election results, geographic information, and company statistics. Due to their coherence to real-world persons and/or households, data privacy is a major concern. In principle, records are made anonymous and often chopped to a representative sample to enable public use (so called Public-Use-Files). Bigger samples exist for scientific purposes (so called Scientific-Use-Files). Data privacy laws regulate access to certain files. Microdata are frequently

distributed in flatfiles (.txt or .csv) or proprietary formats that allow direct import into statistic analysis tools like *SPSS* or *SAS*. Flatfiles are well compressed and do not contain any syntax-overhead like *SQL* structures. In contrast, proprietary file formats enable quick imports due to included data models.

Four key strengths characterize microdata calibration. These strengths determine its attractiveness and use-cases. Additional validation effort pays off in computational models that benefit from one or more of these capabilities. Heterogeneity of Agents is the root cause for most advantages in the application of microdata calibration. Three of the four strengths pay off especially during input validation. Only the first strength relates to output validation as well. The four strengths are:

- *Highest level of validity*: Calibration with the use of microdata ensures a one-to-one relationship to real-world characteristics. The model maps target system states accurately (see comparison outcome II in Fig. 1), while other calibration techniques with the use of random distributions lead to discrepancies to the target system (see results III to V in Fig. 1). Biggest advantages occur if real-world distributions are unsteady.
- *Static initial configuration*: Random distributions and dispersions vary with every simulation repetition. E.g. a specific geographic area might be filled with Agents in the first repetition, while the same area could be empty in the second repetition. Integration of microdata enables static starting points in each repetition. Predictive models that imply sensitivity analyses and/or comparisons of specific snapshots (e.g. census from year 2000 vs. year 2010) profit most from this strength.
- *Diverse parameters per Agent*: Microdata include several variables per record. E.g. census files typically contain hundreds of variables. This fact allows the creation of heterogeneous Agents with various characteristics. Especially econometric models that integrate different real-world parameters benefit from this strength. E.g. a single microdata file can be used to calibrate household size, income, location, and other attributes. Nevertheless, modelers do not need to factor-in all microdata variables in the model's behavior rules. Section 2.6 will present a model that focuses on one parameter (primary attribute), without losing the ability to perform Data Mining on various other variables (secondary attributes).
- *Correlations between variables*: In addition to diverse parameters per Agent, the correlations between these parameters can be transferred into the model. E.g. the two variables income and employment-status might correlate, because employed Agents receive higher income than unemployed Agents. This correlation gets lost if both parameters were distributed independently without the use of microdata.

Despite these advantages, the integration of microdata includes extra requirements and limitations that drive validation effort. One aspect is the availability of microdata. Specific data that fits the model's purpose is required. Data privacy is one of the major barriers for a widespread distribution of microdata. Another aspect are comprehensive data preparation, integration, and encapsulation steps that are necessary. Fig. 4 visualizes these steps. It also presents a screenshot of a typical comma-separated census microdata extract. Each row contains the information about one respondent. The first line is the heading that contains identifiers. For instance, 'ef1' could be a variable that contains the city, normalized via references (e.g. '01' = Berlin, '02' = Munich, etc.). Typically, those references are described in separate metadata descriptions. Metadata includes column names, technical formats (e.g. numbers, strings, etc.), field lengths, and reference lists.

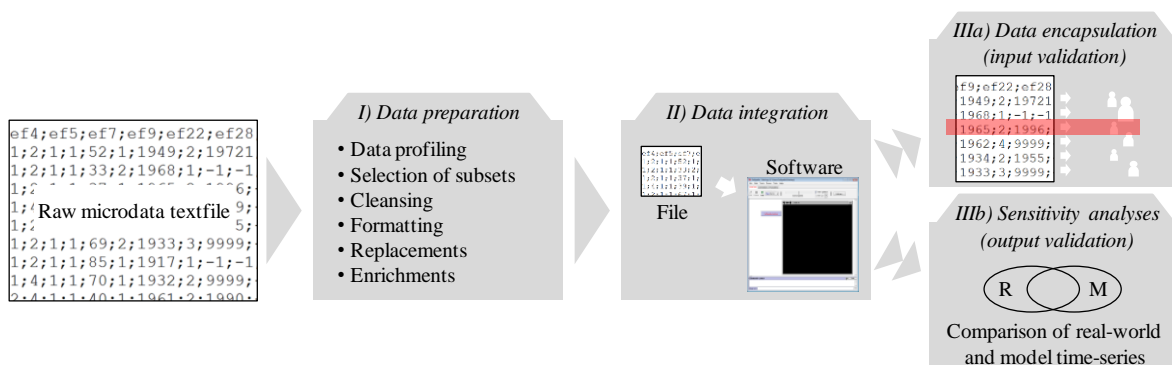


Fig. 4. Microdata preparation, integration, and calibration processes

Step I is necessary to get familiar with data structure and content, modify them with respect to functional and technical requirements, and achieve appropriate Data Quality. Functional requirements include the selection of subsets, if sub-groups best match model requirements. With respect to census data, possible subset-selection criteria could be age, gender, geographic location, or employment status. Technical preparations include re-formatting as well as de-normalization and enrichment with the use of reference lists. Replacements and enrichments are critical, because most microdata files contain problematic values which cannot be imported directly into Agent-based models.⁵ Examples for these values are...

— *NULL values*: NULLs are empty positions in the record-set that contain no information.

Special considerations need to be taken into account when dealing with NULLs, since they are

⁵ Various search-and-replace tasks may be applied to huge text files. The freeware *Text Magician* is suitable to accelerate these tasks enormously (see http://majorgeeks.com/Text_Magician_d5597.html). Furthermore, the tool can split and merge huge files quickly, e.g. to create small samples for testing purposes.

a common source for syntax errors and miscalculations. Not to be mixed up with zeros and spaces.

- *Default values*: Surveys contain questions that are irrelevant for respondents and are skipped. Furthermore, answers may have been refused. Although these kind of information might be valuable for researchers, special treatments are required to ensure an error-free integration into the model. E.g. a net income of ‘9999’ means ‘question skipped’ instead of ‘9999€ per month’.
- *Character set*: Microdata and model files may differ in their character set (e.g. Unicode, ANSI, ASCII, etc.) and require harmonization.
- *Language settings*: Special characters could be in use as separators. Flatfiles frequently use commas to separate values (therefore ‘.csv’ files: Comma separated values), while in many countries commas are used as decimal points.

Data integration is the objective in step II. Prepared data is made available within the modeling tool and within the model. The level of complexity in this step depends on data characteristics and flexibility of the modeling tool. Well-prepared data could be loaded easily by copy/paste, although the tool is inflexible in terms of importing functionalities. Contrariwise, difficulties might occur if high-volume record-sets are squeezed into the model, even if tool functionalities offer built-in importing capabilities. In the best case, both model and tool allow iterative repetitions of the simulation without reloading data. In the worst case, reloading is necessary in advance of each repetition, which usually takes a huge amount of time. The use of small sub-samples is an effective way to reduce programming time and test cycle durations within the modeling stage. In this stage, human interaction is mandatory and support via batch mode functionalities is limited.

As already mentioned at the beginning of section 2.4.2, input and output validation differ entirely in their practical approach (see step III). During *input validation*, microdata information is distributed among encapsulated objects (the Agents). In principle, each Agent receives the information stored in each line from the original textfile. This procedure means direct calibration. For example, a census file may include age, income, and employment status per survey answer. Empirical calibration enables the modeler to create each Agent with these parameters. Validation includes not only the distribution across all Agents, but also the correlation of parameters per Agent. Input validation tasks differ per modeling software. The appendix includes two examples that present encapsulation procedures in *NetLogo*. In contrast to input validation, *output validation* is performed as sensitivity analyses in order to match output time-series with the integrated microdata time-series. Iterative cycles repeat the simulation with varying input parameters until both time-series match. This procedure means indirect calibration. E.g. innovation diffusion

microdata may contain monthly diffusion figures that can be compared to periodic output figures of the model. Complexity through several input parameters will make numerous iterations necessary, until sensitivity analyses result in a suitable configuration.

Microdata input calibration enables researchers to perform Data Mining on output time-series. Enabler is the availability of numerous variables on a micro-level. Typically and in line with the keep-it-simple approach, only a small share of all variables might be queried by behavior rules. The majority of variables is ignored. Still, these *secondary* variables might correlate to outcome indirectly due to dependencies on their *primary* counterparts. E.g. income could be an important behavior input, which depends on employment status and education. With the use of Data Mining, correlations between attributes and their influence on simulation outcomes can be discovered. A combined use of microdata calibration and Data Mining supports modelers in a traditional conflict: Simple models with few variables contribute best to scientific discussions (Axelrod, 1997). In contrast, these simple models often exclude important influencing factors observed in the real-world (Leombruni & Richiardi, 2005). A combination of microdata calibration with Data Mining enables modelers to handle the tradeoff between Axelrod's keep-it-simple principle and the creation of holistic but complex models: Behavioral rules can focus on important (primary) attributes, while dependencies through other variables (secondary) can still be analyzed during *ex-post* Data Mining. Our innovation diffusion model in section 2.6 presents a Data Mining example: Rogers's five adopter classifications (*Innovators*, *Early Adopters*, etc.) are used to cluster adopters. Arithmetic means per cluster produce insights how Agent heterogeneity affects adoption decisions.

2.6 Example: Validating an innovation diffusion model

In this section, we apply the developed maturity matrix to an Agent-based model. We validate the model stepwise by following our two dimensions validation-scope and validation-scale. The replicable *NetLogo* model including code files, documentation, and screenshots are available on <http://www.openabm.org/model/2682>. A stepwise video documentation called '9 Maturity levels in Empirical Validation - An innovation diffusion example' is available online at <http://www.youtube.com/watch?v=qa8KFSKggH4>.

2.6.1 Innovation diffusion in Agent-based simulations

We apply the maturity matrix to a model that simulates product-agnostic innovation diffusion. As *Geroski* (2000) concludes, the Epidemic model and the Probit model were established during the past 60 years as primary diffusion theories. Epidemic spread of information (network effects) drives adoption in Epidemic theory (Rogers, 1976). Contrariwise, utility and positive benefit/cost

thresholds drive adoption in Probit theory. Heterogeneity of adopters is an important influencing factor in the Probit context (Rogers, 2003). Both models result in an ‘S’-shaped cumulative diffusion curve. Bass (1969) derived a logarithmic diffusion pattern based on time-series for consumer durables: The *General Bass Model*. Fig. 5 visualizes this logarithmic growth rate combined with both diffusion models as well as Roger’s five adopter categories. The categories allow analyses with respect to Agent heterogeneity. Adopters within these five groups are divided by adoption timing and differ in several characteristics: In their use of communication channels, readiness to assume risk, and social affiliation (Rogers, 2003).

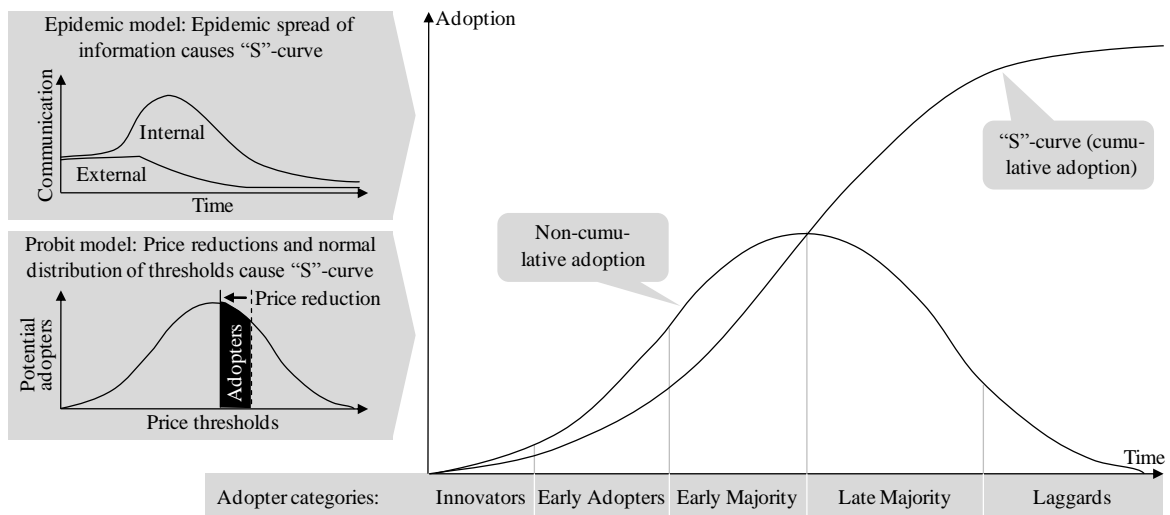


Fig. 5. Diffusion drivers, ‘S’-curve and adopter categories (Geroski, 2000; Mahajan, Muller, & Srivastava, 1990)

The Agent-based methodology is well-suited to simulate innovation diffusion due to its capability to integrate network effects and Agent heterogeneity (Gordon, 2003; Rand & Rust, 2011). It provides advantages compared to differential equation models (Rahmandad & Sterman, 2008) and makes Agent-based modeling a promising venue for diffusion research (Macy & Willer, 2002; Zenobia et al., 2009). Published models underline the capability to combine Epidemic and Probit theories in Agent-based models. E.g. *Cantono and Silverberg* (2009) describe a percolation model in the context of eco-innovations.

Multi Agent-based models enable researchers to include demand *and* supply in a single environment. Our model’s objective is to simulate innovation adoption in such integrated demand-supply environments. The underlying demand function links demand and supply in a single model. The function is determined by learning status (*awareness* for the product) and individual price thresholds (*willingness-to-pay*) of consumers. Furthermore, the function drives market entry and

exit decisions as well as market quantity and price. Put simply, diffusion proceeds if interactions distribute awareness (Epidemic effect) and rivalry reduces the market price (Probit effect). Adoption drives supply-side rivalry and vice versa rivalry determines pricing and therefore adoption. This is important, since intensifying supplier competition has been identified as important influencing factor (Gatignon & Robertson, 1989). It is frequently mentioned in diffusion literature, but rarely modeled in Agent-based simulations. Our paper extends current research by including all three forces in a single model: Epidemic, Probit, and competition. Widely accepted Cournot competition theory is used to model entry, supplier conduct, and price. We will showcase the importance of *endogenous* demand-supply co-evolution. Endogeneity between competitive dynamics and market evolution is under-researched (Safarzyńska & van den Bergh, 2010; Soberman & Gatignon, 2005).

2.6.2 Structure and procedures

Eleven steps sequentially divide the simulation. A loop contains the repeated calculations per time-step. One loop-repetition represents one simulation period and equals one real-world year. The loop is performed iteratively until the exit condition is reached. This condition is a complete shakeout, meaning that all firms left the market. The loop-calculations can be classified into demand-side and supply-side calculations. Fig. 6 plots the end-to-end flowchart in *Unified Modeling Language* (UML).

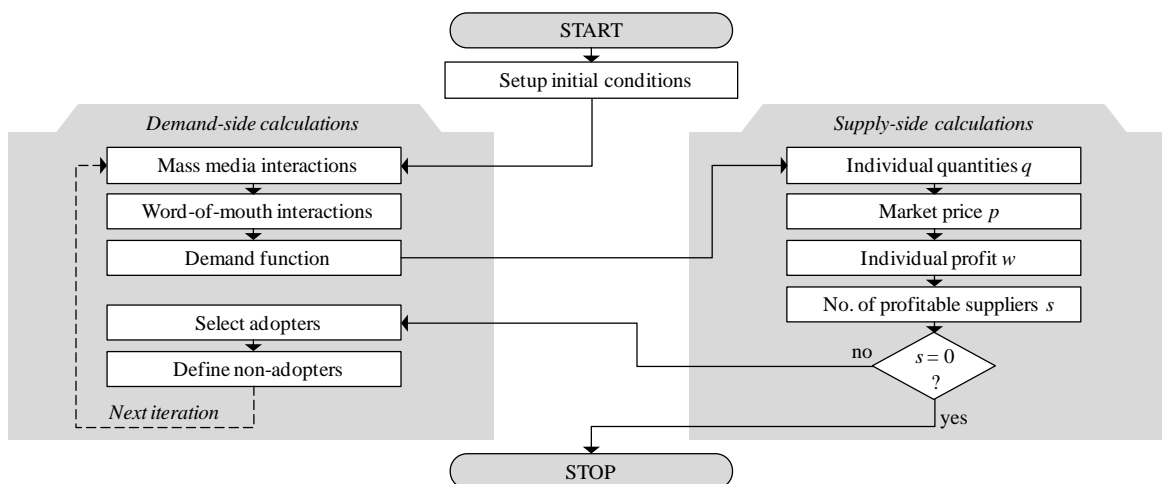


Fig. 6. UML flowchart of model procedures

The simulation starts with an initial configuration that populates the ‘World’ with a set of 10,936 consumer Agents $I = \{ 1, 2, \dots, N \}$ and ten supplier Agents. Consumer Agents change their status

over time: At the beginning, all Agents are unaware (subset I_{unaware}). They turn aware if they receive an interaction (subset I_{aware}). *Constants* and *attributes* are set. Table 2 presents all constants, attributes, and variables. Constants and attributes are static per experiment. *Variables* change periodically, e.g. price p .

Table 2. Parameter overview

Parameter	Type	Description	Value	Comment
N	Constant	Population (no. of consumers)	10,936	Equals the no. of records in census microdata file
C_{var}	Constant	Variable costs	270€	
C_{fix}	Constant	Periodic fixed costs	40,000€	
M	Constant	Periodic mass media interactions	200 ... 800	Is validated indirectly in output sensitivity analyses
H	Constant	Probability of word-of-mouth interaction	0 ... 1	Is validated indirectly in output sensitivity analyses
n(i)	Attribute	Consumer i's no. of neighbors	$\mu=10.5$	Is validated indirectly in output sensitivity analyses
z(i)	Attribute	Consumer i's individual price sensitivity		Is validated directly in input calibrations
a	Variable	Slope-factor of demand function		Demand function: $f = a * p + b$
b	Variable	Constant-factor of demand function		Demand function: $f = a * p + b$
q	Variable	Output quantity of each supplier		
p	Variable	Market price		
w	Variable	Supplier's individual profit		
s	Variable	No. of suppliers		$s = 0$ is used as the trigger to stop the simulation

Demand-side calculations: The adoption-loop begins on the consumer-side with a simulation of external (mass media) and internal interactions (word-of-mouth). Epidemic spread of awareness is the core driver in Epidemic theory. It assumes diffusion to be sparked off by mass media interactions, followed by epidemic rise in word-of-mouth, causing the typical 'S'-shaped curve. External and internal interactions trigger the awareness of consumers in line with theory. Periodically, a fixed amount of M consumers are randomly selected to simulate mass media interactions. In addition, word-of-mouth interactions trigger awareness through imitation. Adopters of former periods (subset I_{adopters}) drive these internal interactions. H determines the probability of one adopter to interact periodically with one unaware consumer within his individual 'Small World'. All interaction-receivers turn aware and are added to subset I_{aware} . The number of aware consumers can be measured as:

$$\sum I_{\text{aware}}(t) = \sum I_{\text{unaware}} \{ 1, 2, \dots, M \} + H * \sum I_{\text{unaware}} \{ 1, 2, \dots, I_{\text{adopters}} \} \quad (1)$$

with n(i) of $I_{\text{adopters}} \geq 1$.

I_{aware} builds the foundation to calculate the eminent demand function $f = a * p + b$. It integrates both diffusion theories by using price thresholds z(i) of aware consumers I_{aware} to calculate demand. To calculate f , all Agents are sorted by z(i) in descending order. Then, a linear regression analysis calculates slope a and constant b with y-value z(i) and the x-value being the order position.

Supply-side calculations: We utilize Cournot theory to calculate competitive dynamics. Cournot competition is a widely accepted economic theory that explains an oligopolistic industry structure in which companies compete on the quantity of output they produce (Besanko, Dranove, & Shanley, 2007). Suppliers share same parameters. This simplifies our model in line with the keep-it-simple principle. Firms produce a homogeneous product, have market power, share identical cost structures, try to maximize profits, and do not cooperate. Suppliers compete in quantities. An essential assumption is ‘Cournot conjecture’: Each supplier maximizes profit w based on the expectation that its own output quantity decision will not have an effect on the decisions of its rivals. Suppliers assume their rival’s quantities to be the same as their own quantity and take the quantity of its competitors as a given. Market price p is set at a level such that demand equals the total quantity produced by all suppliers. We begin with the calculation of output quantity q in dependence of the number of suppliers s :

$$q(s) = (b - C_{\text{var}}) / (-a * (s + 1)) . \quad (2)$$

Followed by the calculation of market price p for each q - and s -combination:

$$p(q,s) = a * (q * s) + b . \quad (3)$$

Knowledge of q and p across all possible supplier situations s allows us to calculate individual profits w :

$$w(p,q,s) = ((p(q,s) - C_{\text{var}}) * q(s)) - C_{\text{fix}} . \quad (4)$$

We now know profit w in case s suppliers compete in the market. Strategic decision making implies that suppliers enter the market to earn profits ($w \geq 0$). Negative profits ($w < 0$) cause competitors to leave. As many profitable suppliers as possible enter the market: s increases step-by-step until another entry would lead to negative profits. Decreasing market potential reduces s and shakeout begins. Order of entry and exit are modeled according to *Klepper’s* (2002) survival patterns. Earlier entrants are assumed to stay longer in the market. With complete shakeout ($s = 0$), the exit condition is reached and calculations stop.

Demand-side calculations (if $s > 0$): After the final decision on the number of suppliers s , the next step randomly selects the total market quantity of $q * s$ adopters from the Agentset I_{aware} whose willingness-to-pay is greater than or equal to market price p :

$$I_{\text{adopters}} = \{ 1, 2, \dots, q * s \} \text{ with } z(i) \geq p \text{ and } I_{\text{adopters}} \in I_{\text{aware}} . \quad (5)$$

The residual aware Agents who were *not* selected are added to $I_{\text{nonadopters}}$. Non-adopters are not eligible for further adoptions.

2.6.3 Simulation results

The software *NetLogo* is used to execute the model.⁶ *NetLogo* is popular among educational modelers due to strengths in usability and documentation (Railsback, Lytinen, & Jackson, 2006). The use of *Logo* as modeling language is a major difference to other tools like *MASON* and *Repast*, which base on common software development frameworks, e.g. *JAVA*, *Python*, *C++*, or *.NET*. As most modeling tools, it lacks out-of-the-box capabilities for the import of high-volume microdata and is restricted due to the principle that the programming code is stored in a single file. Two code examples in the appendix should prove *NetLogo*'s capabilities to integrate high-volume data-sets.

Fig. 7 presents a screenshot of non-validated simulation results. $M = 100$ and $H = 1$ were arbitrarily set. Random calibration of willingness-to-pay with $z(i) < 3,000\text{€}$ resulted in $\mu(z(i)) = 1,499\text{€}$. Overall, 21 time-steps (0 ... 20) were performed until all suppliers left the market ($s = 0$). Blue adopters and yellow non-adopters populate the 'World' (top-left). The Industry Lifecycle shows that up to six suppliers competed in the market. Rivalry induced price reductions below 700€. Cumulative supplier profits confirm the impact of timing and order of entry on firm profitability in growth markets (Parker & Gatignon, 1996): Pioneers spark off innovation diffusion, survive competition until complete shakeout, and earn extraordinary profits. Followers enjoy free-rider benefits but need to handle fierce competition. Late entrants face decreasing market potential due to saturation, survive only a few periods, and earn only small profits. In the innovation adoption context, market potential explicitly decreases when the 'S'-curve crosses the point of inflection. Firms leave the market and shakeout begins.

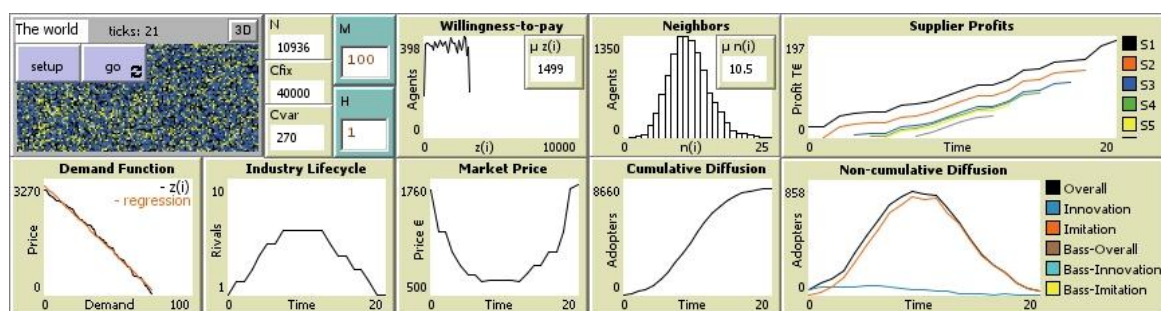


Fig. 7. Simulation results without input or output validation

Both widespread impact theories for the diffusion of innovations—namely Epidemic and Probit—are confirmed within simulation results: Diffusion evolves when mass media kicks off initial awareness of *Innovators* and *Early Adopters* who adopt and cause Epidemic spread of

⁶ See http://en.wikipedia.org/wiki/Comparison_of_agent-based_modeling_software for comparisons of modeling tools.

awareness through word-of-mouth interactions (network effects). The demand-curve shifts to the right (not displayed), appealing more suppliers to enter the market. Monopoly evolves to an oligopoly. Intensifying rivalry reduces the market price, leading to inclining adoption ratios due to the attainment of more Probit price thresholds. Shakeout begins when the ‘S’-shape proceeds to the point of inflection and demand saturation shifts the demand curve back to the left.

2.6.4 Empirical validation

The main purpose of this example is the application of our maturity matrix in a stepwise validation sequence. We perform both input and output validation, focusing on three configurable input factors of the model: Willingness-to-pay $z(i)$ for input validation; Mass media frequency M and word-of-mouth probability H for output validation. The validation order is determined by our preceding comments from sub-section 2.4.3, in which we discussed potential rework effort that occurs if large-scale output validation is performed in advance of input validation. Therefore, we begin with small-scale output validation (grounding) in order to constitute a baseline. We then switch over to input validation and perform the four different techniques from Fig. 3. Finally, we switch back to output validation and perform large-scale sensitivity analyses in order to match M and H with detailed Innovator/Imitator-ratios from the *General Bass Model*. A discussion on the underlying idea to ‘divide and conquer’ and the applied sequence will follow in section 2.7 (jump to Fig. 12 for a helpful preview).

Grounding (M-1): Cumulative and non-cumulative diffusion are utilized as output validation time-series. An exclusive focus on *cumulative* diffusion would make any parameter recalibration unnecessary, because it already presents the typical ‘S’-shape adoption progress (see Fig. 7) in line with the *General Bass Model*. Taking *non-cumulative* diffusion as a second time-series into account, M and H need to be adjusted to map anecdotic diffusion knowledge: Innovation through mass media sparks-off diffusion during the first periods, while Imitation through word-of-mouth spreads awareness epidemically afterwards. We recalibrate M from 100 to 300 to increase the force of Innovation. Vice versa, we reduce H from 1 to 0.5 to engage a smaller impact of Imitation (see Fig. 8). The maturity level of the model evolves from $M-0$ to $M-1$. In case we would pursue general explanatory objectives with the model, maturity would be satisfactorily and we could finish the validation process.

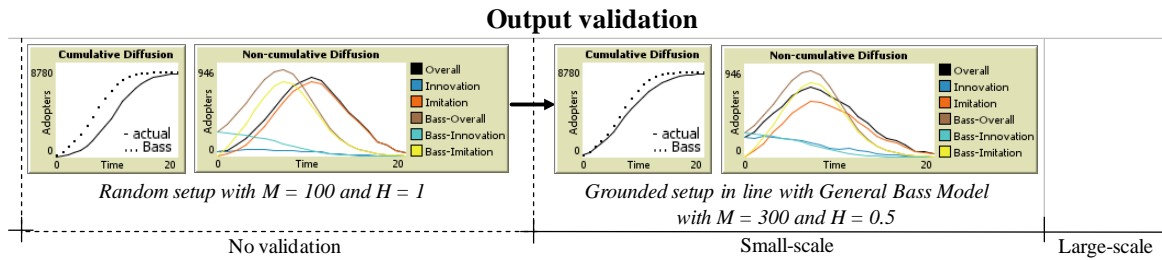


Fig. 8. Initial small-scale output validation (grounding)

The initial grounding of a model is vital to create a baseline configuration that incorporates boundaries for parameter ranges and behavior rules. These boundaries are eminent for sensitivity analyses, because a too broad parameter space would require tremendous amounts of iterations. Furthermore, the boundaries are vital prerequisites for internal validation steps, because otherwise modelers can hardly discover code errors. E.g. the correct functioning of Cournot competition cannot be evaluated within internal validation cycles, if M/H -settings were too low to attract rivals to enter the market.

Small-scale input validation/Approximation (M-4): We continue our validation journey with small-scale input validation of Agent's individual willingness-to-pay $z(i)$. For this example, we assume willingness-to-pay to correlate directly with net income. We calculate arithmetic means for net income from census microdata and apply the resulting value of $\mu = 1,597\text{€}$ to the model.⁷ In a first step, we keep the linear distribution and simply shift the arithmetic mean to the value derived from real-world data (see Fig. 9). Nevertheless, any linear Agent calibration results in huge deviations due to the non-linear income distribution in the real-world (see the graph for 'Microdata calibration' in Fig. 10, which displays an exact plotting of census values). In a second step, we therefore shift from a randomized linear distribution to a randomized normal distribution. Although $\mu(z(i)) = 1,597\text{€}$ keeps unchanged, the number of Agents with a willingness-to-pay between 1,000 and 2,000€ increases remarkable from 3,600 to 8,500. Simulation results show notable changes as well. The demand-curve is much more sensitive in the relevant price range, leading to more volatility with regards to the Industry Lifecycle. Diffusion proceeds faster (16 years), peaks in non-cumulative diffusion are higher (maximum of 1,300 periodic adoptions), and the maximum number of rivals increases from six to eight. The maturity level of the model evolves from M-1 to M-4. In case we would pursue special explanatory objectives—e.g. demand-curve shifts due to co-

⁷ We prepared the German census files 'Mikrozensus 2002' for this simulation example. It is available online at <http://www.forschungsdatenzentrum.de/bestand/mikrozensus/cf/2002/index.asp>. It contains an original amount of 25,137 records on person-level. We stripped these to 11,655 householders and finally received a subset of 10,936 rows after standardizing and cleansing.

evolution of awareness and competition—maturity would be satisfactorily and we could finish the validation process.

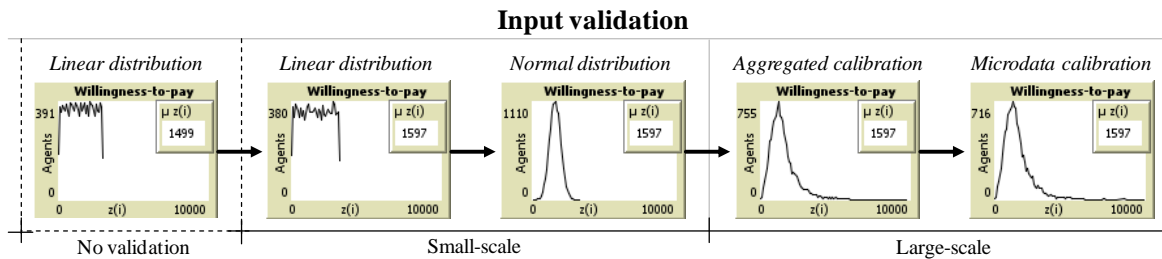


Fig. 9. Input validation sequence from small- to large-scale

Large-scale input validation/Aggregated direct calibration (M-7): Randomized linear and normal distributions are highly efficient calibration techniques. But their effectiveness is limited if real-world distributions are neither linear nor bell-shaped. Especially predictive models require effectiveness through highly accurate and static calibrations. E.g. with the current random normal distribution, only a few Agents with $z(i) > 2,000\text{€}$ exist. Predictive scenario analyses with low competition and high market prices would result in unrealistic and misleading outcomes. We tackle this issue in our third input validation step. We aggregate microdata net income into 24 clusters, count the number of records per cluster, and transfer the results into *NetLogo* by creating as many Agents per interval as counted from microdata. E.g. if 100 microdata records included a net income between 2,000 and 2,300€, we create 100 Agents with a random net income between 2,000 and 2,300€ in the simulation. Calibrations result in a close coherence to real-world microdata (see Fig. 9). The maturity level of the model evolves from M-4 to M-7.

Large-scale input validation/Microdata calibration (M-7): One-to-one mapping of single microdata records and modeled Agents is the objective in the fourth and final input validation step. Instead of aggregated clusters, net income from 10,936 microdata rows is directly integrated into the *NetLogo* model. Validation effort is notably higher, but three arguments to accept this additional effort exist: First, validity reaches its maximum level, which may be required in specific predictive situations. Second, Agent calibrations are entirely static in every iteration. Third, additional variables (in addition to net income) can be integrated into the model, including their real-world distributions and correlations across each other. The eligibility of these reasons varies. E.g. economic models most likely profit from additional analytics (third reason). Data Mining on adopter categories will showcase related benefits in our innovation diffusion example at the end of this section. Reasons one and two gain relevance in predictive simulations that tackle specific markets, networks, or environments. E.g. energy markets and logistic chains.

NetLogo lacks built-in functionalities to integrate high volumes of empirical data. In principle, two possible integration alternatives exist: Direct integration into the programming code and external integration through the import of textfile content. Both alternatives as well as their strengths and weaknesses are explained in the appendix. In our example, the total amount of imported data contained 10,936 rows with 16 variables each. This is still an acceptable volume to integrate the data directly into the programming code. Net income is the only primary attribute, utilized for direct calibration of willingness-to-pay. The set of 15 secondary attributes included demographical information (e.g. age, gender) and socio-economic information (e.g. education and employment details). We will showcase Data Mining examples at the end of this section.

Large-scale output validation/Matching (M-8): We switch back to output validation and tackle the maximum maturity level M-8. Indirect calibration fine-tunes the model. Objective is an exact matching of output time-series with real-world observations—in this case the *General Bass Model*. Indirect calibration differs from grounding in terms of methodology and effort. Sensitivity analyses repeat the simulation numerous times with varying parameter settings until model output and real-world output match. We introduced two error-variables for tracking the deviation of the model's periodic diffusion through Innovation and Imitation in comparison to *General Bass Model* time-series. Error-variables cumulate the quadratic deviations of actual and target values. M and H were re-calibrated iteratively until all ratios match (see Fig. 10) and error-variables were minimal. Although we focus exclusively on M and H as input factors, more than 500,000 repetitions had to be performed to reach this state. 100 repetitions per configuration were necessary to factor-out contingency effects and output dynamics due to random Agent selections (we will follow-up on these desirable dynamics in section 2.7).

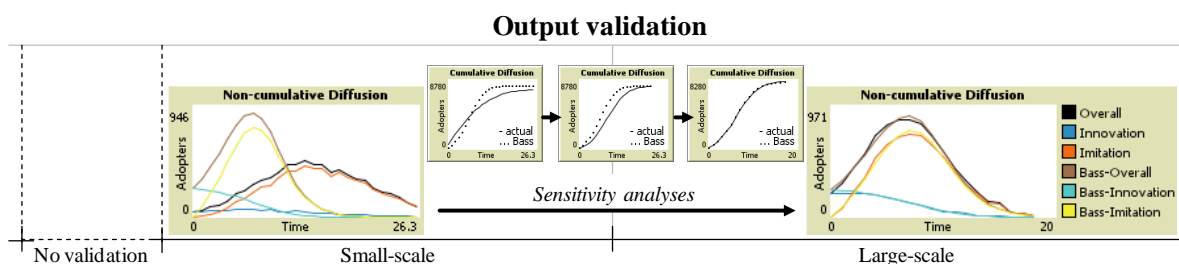


Fig. 10. Large-scale indirect output calibration according to *General Bass Model* results

The maturity level of the model evolves from M-7 to the maximum M-8. Now it could be used for all types of predictive purposes. E.g. forecasting the yearly adoption figures of the technology or analyzing the impact of different policy interventions to induce diffusion. We conclude this

example by showcasing the advantages of combining microdata calibration with Data Mining. Data Mining in commercial marketing typically connects behavioral statistics with individual characteristics of prospects, customers, or lost customers. Through microdata calibration we are able to generate similar statistics, because each of the 10,936 Agents offer an empirically validated demographical and socio-economic background based on 16 encapsulated variables. Agent behavior differs in several measures, e.g.:

- *Awareness*: Agent turned aware yes/no? Through mass media interactions or word-of-mouth? In which point of time?
- *Adoption*: Agent adopted the innovation yes/no? Was it Innovation or Imitation? In which point of time? Induced how many other Agents to turn aware/to adopt? Adoption price?

Data Mining on detailed statistics adds value to the interpretation of simulation outcomes. Autonomous behavior and related influencing factors can be analyzed in more detail. Comparisons between influencing factors enable predictions and explanations of Agent behavior. Table 3 displays exemplary Data Mining results. Statistics include micro-level indicators, e.g. varying Agent states (all/adopters/Rogers adopter categories), as well as different macro-level outcomes, e.g. diffusion-level and diffusion-speed. Varying $n(i)$ values per diffusion-speed of ‘All consumers’ is a nice example of contingency effects. Net income statistics confirm anecdotic diffusion knowledge: *Innovators* accept high prices, while the majority of consumers adopt when prices fall. Income is generally lower with high diffusion-levels, caused by fiercer competition. If more rivals step in, stronger price reductions induce adoptions of consumers whose willingness-to-pay would lead to non-adoption in situations with less competition. The number of neighbors $n(i)$ confirms Epidemic theory. If mass media interacts with Agents who are surrounded by many Agents, more follow-up interactions through word-of-mouth will cause diffusion to proceed faster. *Laggards* have fewer neighbors, include smaller probabilities to receive an interaction, and therefore adopt at the end of the innovation lifecycle. Table 3 displays two secondary attributes to show the capability of microdata calibration to exclude certain parameters from behavior rules without losing the ability to include them in complex *ex-post* analytics. The number of weekly working hours as well as apartment size correlate with net income. These correlations influence final statistics per adopter category.

Table 3. Exemplary Data Mining results

Agent characteristics	All consumers	All adopters	Adopter categories				
			Innovators	Early Adopters	Early Majority	Late Majority	Laggards
Diffusion-level			Net income (in €)				
72%	1,597	1,822	2,294	1,813	1,760	1,765	2,007
73%	1,597	1,805	2,007	1,818	1,751	1,760	1,974
74%	1,597	1,802	1,976	1,824	1,748	1,754	1,969
75%	1,597	1,794	1,933	1,827	1,721	1,759	1,976
Diffusion-speed			No. of neighbors				
17 years	10.49	10.58	10.52	10.75	10.88	10.58	9.86
18 years	10.47	10.57	10.45	10.78	10.85	10.56	9.82
19 years	10.47	10.56	10.47	10.76	10.84	10.56	9.79
20 years	10.45	10.54	10.44	10.72	10.82	10.55	9.79
21 years	10.40	10.44	10.27	10.62	10.59	10.53	9.81
Secondary attributes:							
No. of weekly working hours	38.89	39.77	40.31	39.82	39.60	39.61	40.27
Apartment size (in m ²)	88.81	92.72	96.19	93.08	91.72	91.83	95.87

Data Mining on secondary attributes could be used for different explanatory and predictive purposes. E.g. demand forecasts could help marketing managers with the optimization of marketing campaigns. Product managers could profit from target group analyses and include related needs and behavior findings into product development and product marketing activities. Finally, the enabler for all these benefits is microdata calibration. As *Axelrod* (2003, p. 6) states: “The complexity of agent-based modeling should be in the simulated results, not in the assumptions of the model.”

2.7 Discussion and propositions

This section discusses our most important findings from sections 2.3 to 2.6 and summarizes them in six propositions. Authors frequently state that their Agent-based model is empirically validated, but the term is flexible as the contradictory approaches in this paper show. How do validation approach and model’s objective fit? Which input factors have been validated? How accurately were real-world data integrated? We suggest other researchers could leverage our maturity matrix to answer these questions. We compare validation methods and derive their maturity based on potential tolerances of validated figures, deviations per repetition of the same model, and discrepancies to the real-world. These comparisons are perhaps our most valuable research contribution. Discussions on benefits and challenges per taxonomy allow modelers to select the most promising method in terms of effectiveness (validity) and efficiency (validation effort). Furthermore, readers of Agent-based studies are equipped with a scorecard to evaluate applied validation techniques and ultimately understand the author’s intention to choose one method instead of another.

As our stepwise innovation diffusion example shows, validation approaches differ remarkably in terms of effectiveness and efficiency. Complex microdata calibration causes huge validation efforts and makes numerous iterations (e.g. sensitivity analyses) challenging compared to simple randomized configurations. Nevertheless, both approaches may result in equal time-series in case of linear or normal empirical data distributions. Furthermore, many models do not profit from sophisticated and highly accurate microdata validation, because their primary objective is to explain emergent effects from the bottom-up. These models require only low maturity levels. Grounding is the best-suited taxonomy. Maturity requirements are difficult to standardize. Minimum requirements differ per model, as our explanations and examples show. We derive proposition P1 from these findings:

P1: Validation requirements differ between Agent-based models. The best-suited empirical validation approach depends on (i) the model's objective and (ii) the available empirical data.

We used a straightforward distinction between two fundamental modeling objectives: Explanation and prediction. These two objectives cover the majority of published Agent-based models. *Epstein* (2008) discusses a variety of further objectives, e.g. the guidance of data collection and the training of practitioners. In order to cover a broad range of applications, we split the two categories into more detailed sub-categories. Fig. 11 visualizes these sub-categories and presents our maturity-related conclusions:

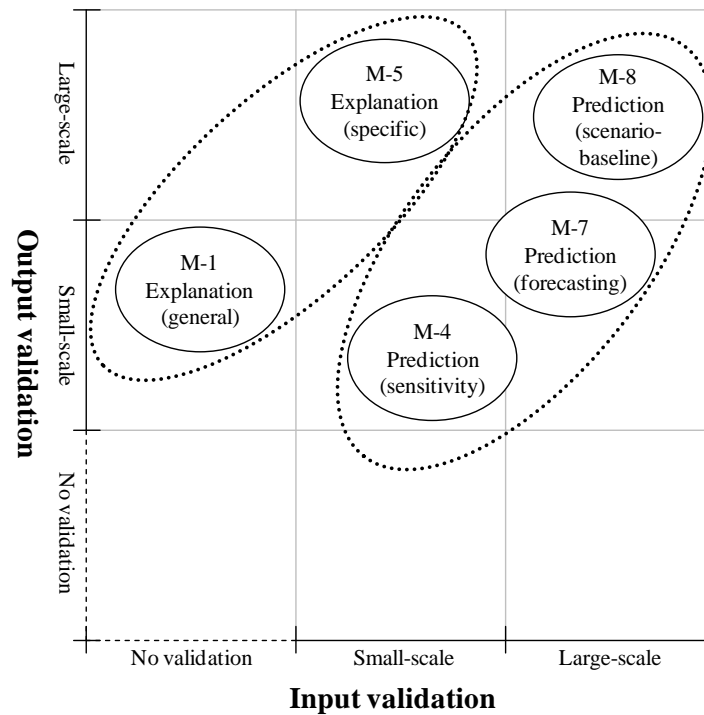


Fig. 11. Maturity requirements per model objective

Explanatory models explain specific real-world observations in a virtual environment. The Agent-based paradigm is well-suited to explain a huge variety of observations, because many real-world effects emerge from the bottom-up: Traffic jams, stock market crashes, epidemics, climate change, search engine algorithms, game theory, and other effects.⁸ We distinguish between two types of explanatory objectives:

- *General*: Explanation of general knowledge usually includes only a small number of parameters. Modelers focus on high-level results and not on the exact figures, e.g. the occurrence of an ‘S-’shaped innovation diffusion curve. Small-scale output validation (grounding) is adequate.
- *Specific*: Tackling of differentiated real-world observations requires proper input factors in order to isolate causal chains. Typically, very specific validation data is utilized to match model outcomes exactly with empirical statistics. E.g. researchers use specific explanatory Agent-based models to re-engineer, explain, and showcase emergent effects they previously measured in their own empirical studies.

We derive proposition P2 from our findings:

⁸ See <http://ccl.northwestern.edu/netlogo/models> and <http://www.openabm.org/models> for various examples.

P2: Explanatory models require lower maturity levels compared to predictive models. Output validation is best-suited to validate explanatory models.

On the contrary, models for predictive purposes embody fundamentally different validation requirements. Such models are characteristically more complex and include a higher number of parameters, because complex real-world activities should be mapped as realistic as possible. Furthermore, the significance of model outcomes relies completely on the model's maturity level. Predictive models are useless without high validity, because (Agent-based) simulations simply calculate pre-configured procedures based on pre-configured variables. Garbage-in, garbage-out. Researchers need to validate all relevant input factors or need to decide which input factors could base on assumptions without jeopardizing the credibility of the model. As with explanatory models, validity requirements differ between sub-categories. They basically belong to one of the following types:

- *Scenario analyses*: A fully validated baseline configuration constitutes a basic setup. Further configurations that diverge in one or more parameters constitute scenarios. Scenario results are compared to the baseline. Typical applications are policy simulations and varying market conditions (best case, worst case, etc.).
- *Forecasting*: Only one focused model configuration is used to forecast future developments. Typically, unique empirical data is applied to answer very specific research questions. E.g. the yearly diffusion of an eco-innovation.
- *Sensitivity analyses*: Models include two sets of input factors. First, a set of validated calibrations that determine fundamental model behavior. Second, a set of non-validated parameters that is iteratively changed within a pre-defined parameter space. E.g. a biologic model that simulates epidemics could be repeated with various population densities, until the threshold reaches a critical mass for contagion effects.

Predictive models rely on high validity through input validation. Three of the four key strengths of microdata calibration apply only with input validation. Output validation is naturally less important or even contradictory, due to the fact that researchers are interested in detailed values of output time-series. Large-scale output validation reduces the ability to predict developments and measure unexpected outcomes, because developments and outcomes were configured *a priori*. 'You get what you measure'. Researchers would jeopardize their main reason to build a predictive model through comprehensive output validation. One exception exists, as our stepwise innovation diffusion example shows: The baseline calibration in the context of scenario analyses. Baselines need to be as realistic as possible with the highest level of validity. Extensive validation is

mandatory. Scenarios build upon the baseline with varying input factors in order to tackle research questions that analyze the impact of these variables. Behavior rules are rarely changed. We derive our conclusions for predictive models in proposition P3:

P3: Predictive models require higher maturity levels compared to explanatory models. Input validation is best-suited to validate predictive models.

The achievement of high maturity levels is challenging. It requires huge validation efforts, as our stepwise example confirms. Missing importing capabilities in Agent-based simulation software further complicates the process. We suggest researchers to follow a ‘divide and conquer’ approach. Our maturity matrix serves as a sub-structure. In a first step, the non-validated model (M-0) should be grounded (M-1). Grounding is the best starting point. It enables modelers to...

- evaluate the effectiveness of the model (is it qualified to fulfill the proposed explanation/prediction purpose?),
- perform internal validations (are functional requirements correctly transformed into executable code?),
- bound parameter configurations to plausible ranges (good preparation of input validation steps),
- evaluate the influence of each input factor (how strong does each factor drive model outcomes?),
- gain insight about causal chains within the model, and
- perform plausibility checks for scenario analyses (do outcomes change in the expected way if specific parameters change?).

Most researchers perform simple output validation instinctively. Their preliminary expectations usually base on anecdotic knowledge. In addition, identification of functional errors in the programming code (internal validation) is almost impossible without grounding. E.g. a model could run forever, because the programming code for stop commands contains errors (internal validation necessary) or because empirically calibrated stop triggers mismatch simulation thresholds (external validation necessary). Without grounding that bounds parameter settings, the modeler can hardly distinct both root-causes.

The next steps of the ‘divide and conquer’ approach focus on input validation (M-4 and M-7). We propose modelers to finish all input validation stages before switching back to output validation. Fig. 12 visualizes this suggestion in an overall sequence. We already explained the two primary reasons why input validation should be finalized in advance of large-scale output

validation in section 2.4: First, parameters are directly calibrated within input calibrations and therefore lead to higher validity. This is critical in case of conflicting calibrations, if output validation leads to different configurations than input validation. In these cases, the direct input configuration should be applied. Second, even small changes of input factors (variables, behavior, and world conditions) require a repetition of the entire large-scale output validation procedure. In contrast, direct calibrations are stable setups. Changes in one parameter will not affect the validity of other parameters. Our proposed sequence helps modelers to reduce rework to a minimum.

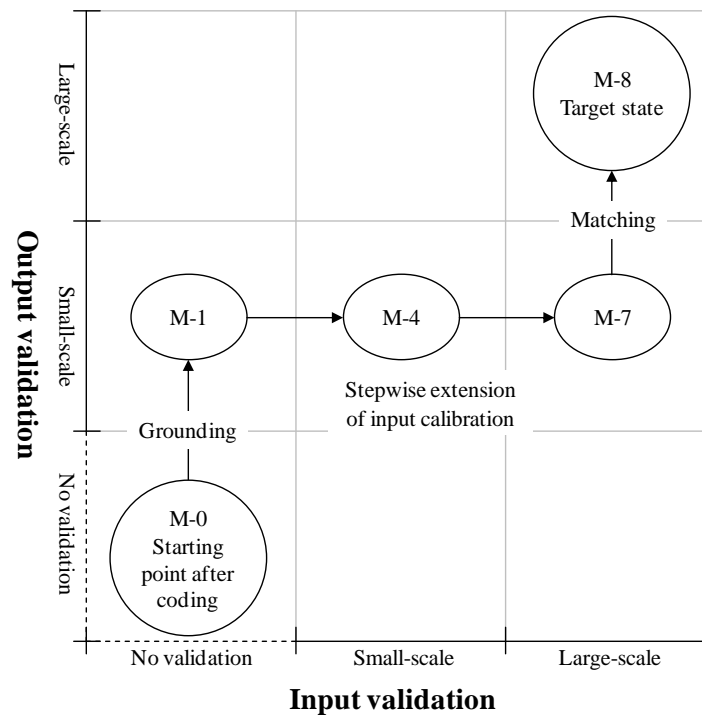


Fig. 12. Proposed ‘divide and conquer’ validation sequence

Matching (M-8) is the final step. Only a few reasons to perform both large-scale input and large-scale output validation exist. As in our example, configuration of a baseline configuration is the most frequent reason. It is challenging mainly because of three reasons. First, yet-to-be-acquired data is often necessary to validate predictive models, as *Tesfatsion* (2010) describes in her *prescriptive output validation*. Second, time-consuming sensitivity analyses need to be performed in order to identify the ‘sweet spot’ configuration that best-matches real-world data. Depending on the number of input factors, several thousand or even millions of iterations are necessary. E.g. our sensitivity analyses on two variables (H between 0.2 and 0.8 in intervals of 0.05 and M between 200 and 600 in steps of 1) and with 100 repetitions per configuration to factor-out contingency

required more than 520,000 model executions. About 6,000 runs per hour could be performed on a laptop with *Intel Core i5* processor (4 kernels and therefore 4 parallel runs) and 4 gigabyte RAM. Overall runtime was 3.5 days. Even worse, huge proportions of sensitivity results become useless if any input factor is changed (rework). Third, further challenges arise if there is not a single ‘sweet spot’ but multiple, which is very often the case. The researcher needs to pick one configuration to promote it as *the* optimum setup. Proposition P4 concludes the explained sequence and its underlying trade-off between effectiveness (validity) and efficiency (validation effort):

P4: Modelers should ‘divide and conquer’ their validation steps. An effective and efficient validation sequence (i) starts grounding, (ii) then focuses on direct input calibration, (iii) and finishes with indirect output calibration.

Avoided rework and higher validity are not the only advantages of input validation compared to its output-related equivalent. Researchers should ask themselves why they selected Agent-based modeling as their research methodology. The majority of answers will stress bottom-up analyses, emergent behavior, and parallels of emergent effects in the real-world. Many Agent-based models profit from Agent heterogeneity and network effects (Agent interactions). Without at least one of these two aspects, other methodologies may be better suited, e.g. linear algebra (Rahmandad & Sterman, 2008). Heterogeneity and network effects naturally and intentionally lead to deviations in output time-series. Contingency is a determining factor in this context. Especially random Agent selections lead to instable and unexpected results. E.g. innovation diffusion evolves slowly in our example, if Agents with low adoption probability and small neighbor-counts are randomly selected during the first simulation periods. Vice versa, diffusion skyrockets if these potential *Innovators* and *Early Adopters* included opposite characteristics. A vivid example for instability is the ‘Wolf Sheep Predation’ model⁹: Sometimes sheep survive; sometimes wolves outlast sheep and then die due to missing prey. Sheep/wolf-population ratios may rotate in the process. We evaluate these dynamics to be highly desirable in Agent-based modeling. Large-scale output validation requires stable results and jeopardizes these dynamics. Modelers could be misguided through indirect calibration and induced to eliminate dynamics and contingency. A compromise is included in our example: We keep the dynamics in emergent behavior and accept varying error-factors (deviations between model output and the *General Bass Model*). Output validation is performed on the arithmetic mean from 100 repetitions per configuration. We derive proposition P5 from our findings:

⁹ See <http://ccl.northwestern.edu/netlogo/models/WolfSheepPredation>.

P5: Input validation is superior in balancing validity and emergent dynamics. Arithmetic means from numerous repetitions enable output validation despite contingency and instability of outcomes.

We devoted huge parts of this paper to microdata calibration. This highly accurate and granular method is rarely discussed from a methodical perspective, although it has been applied in several predictive occasions. We see great potential for microdata calibration to perform large-scale input validation in the context of Agent-based computational economics. Availability of empirical data is one driver, as our census data example shows. Another driver originates from the fact that microdata calibration results in the highest level of validity. A third driver arises from the conflict between input factor complexity and the requirement for simple and replicable models. Microdata calibration enables modelers to adopt the keep-it-simple principle and use only a few validated input parameters (primary attributes) without losing the ability to analyze further and potentially correlating parameters (secondary attributes). Our innovation diffusion example encapsulates 16 census variables to configure and validate a comprehensive socio-economic background per Agent. Only one attribute triggers simulation outcomes. We perform Data Mining on micro-level output time-series like in commercial marketing. Data Mining gains insights about correlations between autonomous *behavior* and individual *attributes* of Agents. A split into primary and secondary attributes enables modelers to focus on a handful important primary variables without losing the opportunity to display impacts of secondary characteristics. Extensive ways to slice results are possible without inflating the model (e.g. split into adopter categories and their characteristics). Similar to large-scale output validation, Data Mining requires numerous simulation repetitions to generate solid results, because contingency effects influence model outcomes. These effects, e.g. random Agent selection as in our example, vanish after hundreds or thousands of simulation repetitions. We derive our last proposition P6 from microdata findings:

P6: Calibration with the use of high-granular microdata leads to highest validity. It is best-suited in the context of direct input validation. A combined application with Data Mining on output time-series helps researchers to keep models simple.

A few limitations and follow-up discussions need to be considered. Our maturity evaluations try to cover a broad range of applications and include a straightforward categorization into small-scale and large-scale validation techniques. Two questions arise: First, where is the exact boundary between small- and large-scale? Our distinction is guided by our approach to work with or without

microdata, which offers a solid borderline. In contrast, the number of validated parameters is a vague distinction. How many variables need to be validated to consider a model to be large-scale validated? 50%? 75%? 100%? The second fundamental questions relates to the order of maturity levels. We clearly distinct between two dimensions and assume input validation leading to superior maturity compared to output validation. But is input validation always dominant? This may be questionable in some occasions. E.g. is large-scale output validation (M-2) less mature than approximation (M-3)? Another discussion point is the integration of *cross-validation* into the maturity matrix. Cross-validation compares a model with other models and may result in empirical validation, if the counterpart has been externally validated (Rand & Rust, 2011).

With regards to microdata calibration, we see particular necessity to develop standardized procedures and functionalities to integrate microdata into Agent-based simulation tools. The immense data preparation, integration, and encapsulation efforts build huge obstacles for the adoption of this promising validation technique. Our step-by-step example covers just a few preparation activities. Other data may require extensive and more complex cleansing, enrichment, normalization, and/or formatting steps. Handling of high-volume record-sets exponentially increases the complexity across these activities. The import of huge record-sets is almost impossible with many software tools. Slow file-read functionalities and the unnecessary need to reload microdata afore each simulation repetition make sensitivity analyses virtually impossible. In order to promote the integration of microdata without explicit software functionalities, we provide two coding alternatives in the appendix. One alternative integrates the data directly into the model code, resulting in a remarkable acceleration of encapsulation procedures and experiment repetitions.

2.8 Conclusion

This study outlines a variety of external validation techniques for Agent-based models. Empirical validation is a major concern across academia, but comparisons between techniques are rarely published and under-researched. Fundamental sub-structures that are based on a holistic view are missing. There is demand for such reviews and frameworks since validity is one driver for its circulation of Agent-based methodologies in literature. Reviewers and readers typically face challenges in...

- estimating validation requirements per model,
- understanding the applied validation approach itself,
- evaluating potential alternative taxonomies and their pros and contras, and
- estimating the resulting level of validity.

This paper tackles these issues and reviews, compares, and categorizes different approaches in order to promote the Agent-based methodology. We develop a maturity matrix to create an underlying sub-structure that embodies two decisive factors: Validation-scope and validation-scale. Furthermore, we explain the nine maturity levels in detail, discuss compatible applications, underpin our concept through the stepwise validation of an innovation diffusion example, and conclude our findings in the form of six propositions.

What do we learn from this paper? First and foremost, we confirm the complexity of the research area. A variety of differing validation taxonomies exist, with contradicting impacts per model objective. E.g. explanatory models may benefit from large-scale output validation, while the same approach jeopardizes the objectives and output dynamics of predictive simulations. ‘One size does not fit all’. The best-suited validation approach depends on the model’s objective and the available empirical data. We suggest researchers clearly state the model’s purpose, how and why they validated each input factor, and how validation affected the outcome.

Furthermore, we suggest researchers stick with the keep-it-simple approach to avoid over-parameterization. Too many models contain horrific amounts of parameters. Deterrent examples exist: Some models contain such volumes of variables, that these parameters do not fit into the paper’s methodology section and fill full-page tables in the appendix. It is virtually impossible to validate and/or replicate such models. Handling of complexity is *the* core capability in Agent-based modeling. But its root-cause originates from Agent heterogeneity and network effects, not from parameter overflow-handling. We present a microdata calibration technique to showcase a method that allows highest validity levels and utilizes core capabilities of Agent-based modeling: Heterogeneity, bottom-up economics, and output dynamics.

2.9 Appendix

2.9.1 Direct microdata integration in *NetLogo*

NetLogo lacks built-in capabilities to integrate high volumes of microdata. In this appendix, we present two different ways to create and calibrate Agents based on imported microdata. The first way pastes all microdata records into the *NetLogo* code. No external file is required, therefore this method is advantageous if the model should be published on a webserver or needs to be sent via E-Mail. Performance is a second strength compared to file-read approaches. Setup processes run faster, because the code is pre-loaded into the RAM without hard disk input/output activity. This is critical in case of sensitivity analyses with thousands of iterations. The following code includes six

microdata records with 16 variables per record, creates Agents, and encapsulates one line of microdata to each Agent:

```
set microdata [
  [ 53 1 1 2 844 52 8 98 -1 5 9 1 1211 400 -1 8 ]
  [ 61 1 8 -1 -1 -1 -1 -1 -1 1 5 4 2374 400 -1 15 ]
  [ 51 2 8 -1 -1 -1 -1 -1 -1 -1 -1 2 1059 10 -1 6 ]
  [ 45 1 1 6 51 20 8 40 -1 1 -1 1 1134 10 0 7 ]
  [ 70 1 8 -1 -1 -1 -1 -1 -1 1 -1 3 1462 10 -1 8 ]
  [ 29 1 1 6 481 45 8 35 -1 1 3 1 1588 10 -1 9 ]
]
foreach microdata [
  create-turtles 1 [set attributes ?]
]
```

2.9.2 External file integration in *NetLogo*

Direct code integration is problematic with huge microdata files and if the data needs to be modified. File sizes would explode and *NetLogo* may collapse. Simple copy/paste integration can be utilized with small record-sets. But in computational economics, files typically include huge volumes of empirical respondents (rows) and variables (columns). The better option is an external file which is loaded during the setup stage of the model. The following code reads the tab-delimited text file 'microdata.txt', assumes 16 variables per record, and populates the microdata variable until the cursor arrives at the end of the text file:

```
file-open "microdata.txt"
set temp []
while [file-at-end? = FALSE] [
  while [length temp != 16] [set temp fput file-read temp]
  set temp reverse temp
  set microdata lput temp microdata
  set temp []
]
file-close
```

```
foreach microdata [  
  create-turtles 1 [set attributes ?]  
]
```

The fifth line includes an important code fragment for high-volume microdata imports: A combined use of ‘fput’ and ‘reverse’ commands. This command increases importing performance radically, because *NetLogo* uses singly linked lists (see *NetLogo* manual for detailed information). On low-performance hardware or with data tables exceeding hundreds of megabytes, ‘fput’ and ‘reverse’ are necessary to enable acceptable performance.

3. Policy Induced Diffusion of Innovations¹⁰

3.1 Abstract

Three policies to induce innovation diffusion were simulated: Market liberalization, information policies, and monetary grants. Varying options for targeting, timing, and scaling were tested across these interventions. Adoption forecasts differ in effectiveness (speed and level) and efficiency (costs and welfare). One size does not fit all. Informational interventions accelerate adoption, but loose effectiveness in monopolies and with late timing. Monetary grants boost speed and level, but policy costs as well. Market structure is critical: Interventions in closed markets primarily favor the monopolist. Intensifying competition is an effective and efficient diffusion driver. Ten propositions conclude our findings. Regulators should combine policies to gain synergies and utilize strategic decision making of suppliers. Methodically, a product agnostic and empirically validated Agent-based model is applied. Consumers adopt due to Epidemic awareness-spread and attainment of Probit price thresholds. Suppliers act strategically upon Cournot competition. Supply-demand co-evolution integrates both actors endogenously. Video documentation and public availability of the model should encourage other researches to replicate.

3.2 Introduction

Diffusion of innovations has been an important field of research for decades, focusing on product and process innovations as major sources for creative destruction (Banbury & Mitchell, 1995). A variety of solid explanation models, drivers, and categorization frameworks have been developed (Geroski, 2000). These frameworks typically build upon empirical observations to explain autonomous adoption procedures. But in the last couple of years, a new research area was established: *Induced* diffusion of innovations. Regulators actively intervene in the diffusion procedure in order to artificially boost adoption-speed and adoption-level (Diaz-Rainey, 2009). Concern in this research area was developed due to recent inducements of ‘Green’ technologies: Climate protection initiatives and CO2 abatement goals require fast and widespread diffusion of e.g. organic fuel E10, photovoltaic, electric vehicles, and combined heat and power. ‘Green’ innovations are typically disruptive and may cause competitive advantages for economies (Christensen, 2000; Christensen et al., 1998). But design of effective and efficient inducements is

¹⁰ Rixen, M. & Weigand, J. (2012). Policy Induced Diffusion of Innovations. Unpublished manuscript.

difficult. Wrong decision making may cause non-adoption and/or uncontrollable costs. For instance, the German regulator *Bundesnetzagentur* failed to induce *Smart Metering* diffusion through market liberalization, because no competition developed. Contrariwise, its feed-in tariff approach pushed photovoltaic too effective: Diffusion synergies through extensive media coverage and economies of scale cause out-of-control policy costs. Allocation of these costs substantially increases electricity bills of every household. In general, policy makers typically face obstacles selecting the optimal intervention...

- *type* (e.g. market liberalization, information policy, monetary grant, or some combination thereof),
- *targeting* (e.g. geographical focus or adopter subgroup),
- *timing* (start-time and duration),
- *scale* (e.g. small vs. large magnitude).

This paper's objective is to evaluate policy options to induce adoption. We utilized an empirically validated and integrated demand-supply model that bases upon widely accepted diffusion models (namely Epidemic and Probit) as well as economic theory (Cournot competition). Utilizing Agent-based modeling enabled us to combine consumer adoption drivers in the form of network effects and adopter heterogeneity with strategic decision making of suppliers. Addressing a common shortfall in previous innovation work, we close the loop between innovation diffusion and industrial organization theory and verify the endogeneity between market evolution and competitive dynamics (Soberman & Gatignon, 2005).

Scenario and sensitivity analyses give insight on different policy options as well as targeting-, timing-, and scaling-options. Results focus on their effectiveness (speed and level) and efficiency (policy costs and welfare effects). Findings contribute to the ongoing discussion about which policy framework is best-suited per innovation diffusion scenario. A variety of further scenarios isolate specific adoption drivers, confirm their impact, and guide future research on new and promising policy options. Our predictions should support lawmakers in the design of effective and efficient policies that leverage competitive dynamics, boost adoption-speed and -level, and combine interventions to gain synergies.

We begin with literature reviews on adoption drivers that guided our methodology and policy design. Section 3.4 elaborates the Agent-based model. Section 3.5 presents simulation results and ten propositions on effective and efficient policies. Section 3.6 includes a discussion of the results. In section 3.7 we provide some concluded remarks and present future research directions.

3.3 Literature Review

Innovation diffusion has been an interdisciplinary field of research for several decades. In 1969, Bass published a common pattern for the adoption of innovations (Bass, 1969). It was based on generalizations of empirical diffusion data for consumer durables, e.g. fridges, TVs, tumble driers, and air conditioners. His *General Bass Model* describes cumulative adoption as an ‘S’-curve (see Fig. 13). This scheme was developed further in later works (Bass, Krishnan, & Jain, 1994; Mahajan & Muller, 1979; Mahajan, Muller, & Bass, 1995a). Two indicators measure the performance in this scheme: *Speed* and *level* of adoption. In this study, we utilize both indicators to evaluate effectiveness of policy options to *induce* diffusion. Induced diffusion tackles questions of how regulatory interventions accelerate the adoption process (speed) and how they increase the long term penetration rate (level) (Diaz-Rainey, 2009). Consumer durables with short product lifecycles, high risk to be imitated, and/or huge development effort rely on fast *speed*. A quick attainment of the critical mass is crucial: From this point, enough individuals adopted the new product to induce a self-sustaining continued adoption (Rogers, 2003). On the contrary, *level* describes the innovation’s penetration rate (a.k.a. saturation). Some products gain huge shares in the target market, e.g. *Microsoft Windows*. While others, e.g. *Linux*, attract specific subgroups and reach only small levels. Target groups and their adoption timing are primarily determined by *heterogeneity* of adopters. *Rogers* established five adopter categories that describe and explain impacts of heterogeneity on adoption decisions (Mahajan et al., 1990). These five categories are divided by adoption timing (see Fig. 13). Adopters in each category differ in several characteristics, e.g. in their communication channels, readiness to assume risk, and social affiliation (Rogers, 2003).

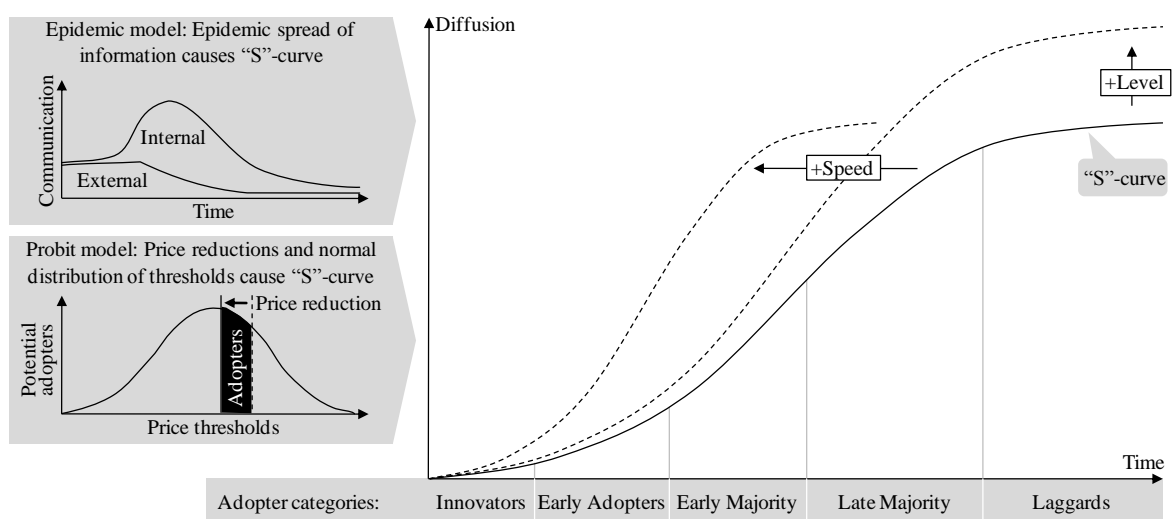


Fig. 13. Diffusion drivers, ‘S’-curve and adopter categories (Diaz-Rainey, 2009; Mahajan et al., 1990)

Our objective is to extend current diffusion research by simulating policies. We arrange the policy design in this study by the fundamental influencing factors that drive speed and level of adoption. Depending on the direction of influence, these factors can also lead to the formation of barriers hinder adoption. *Geroski* reviews according fundamental influencing aspects (Geroski, 2000). We conclude that state-of-the-art models as well as effective and efficient policies require to embody Epidemic and Probit aspects:

- *Epidemic*: Information transmission through *network effects* is vital in Epidemic models. Learning drives adoption. The ‘S’-shape results from contagion effects in interactions. Awareness rises exponentially when word-of-mouth of *Innovators* and *Early Adopters* trigger the awareness of residual buyers (Rogers, 2003). The *General Bass Model* is a famous Epidemic model. *Bass* explains the ‘S’-shape occurrence through a shift from external influence (mass media) to internal influence (word-of-mouth) (Mahajan et al., 1990). We setup scenarios with *informational policies* that induce external interactions.
- *Probit*: Probit models stress benefit-cost-thresholds, a.k.a. Probit thresholds. Utility drives adoption. Attainment of positive benefit-cost-ratios creates demand. The ‘S’-shape is explained via normal distribution of Probit thresholds in combination with price reductions over time (Geroski, 2000). For instance, costly phone tariffs prevent cutting edge cell phones to diffuse. Adoption kicks off when cheaper tariffs are launched that match willingness-to-pay of the mainstream. Frequent sources for price reductions are learning curves and economies of scale. Search costs, switching costs and opportunity costs may influence perceived utility. Economic risk and technical complexity create barriers that postpone the adoption or even cause resistance of potential adopters (Kleijnen, Lee, & Wetzels, 2009). We setup scenarios with *monetary policies* in the form of purchase bonuses for consumers.

Supplier competition is another influencing factor in the innovation adoption process. Intensifying competition induces adoption, leading to a more rapid and higher level of diffusion (Gatignon & Robertson, 1989). It is rarely mentioned in literature compared to Epidemic and Probit models which appear frequently. We see competition not as a third driver, because the influencing root-causes are cost and price reductions since suppliers compete in quantities or price (Robertson & Gatignon, 1986). Competition models and Probit models are very similar. We see competition as an important building block to calculate market quantities and prices in diffusion models. Our paper extends current research by including all three forces in a single model: Epidemic, Probit, and competition. Contribution is leveraged by the use of widely accepted Cournot competition theory to model entry, supplier conduct, and price. Market structure is critical. A shift from

Monopoly to Oligopoly causes sales to take off (Bayus, Kang, & Agarwal, 2007). As a result, we incorporate *market liberalization* as one policy option.

Examples of models that factor-in Epidemic and Probit effects exist. E.g. *Cantono and Silverberg* describe a diffusion model in the context of eco-innovations (Cantono & Silverberg, 2009). Nevertheless, current models lack competitive supply-side dynamics, although findings showcase the importance of an *endogenous* relationship between supply and demand: Epidemic consumer awareness-spread increases sales potential, firm entries become profitable, rivalry ends up in Probit effects leading to innovation adoption (Vettas, 1998). Endogeneity arises when adoptions trigger the awareness of other potential adopters. These endogenous links between competitive dynamics and market evolution are under-researched (Safarzyńska & van den Bergh, 2010; Soberman & Gatignon, 2005). We explicitly tackle these links in our model to contribute current research via supply-side dynamics.

Timing and *order of entry* drive firm profitability in growth markets (Aaker & Day, 1986; Lilien & Yoon, 1990). Consideration of first-mover advantages and follower strategies is crucial to understand competitive dynamics (Klepper, 1996, 2002). Pioneers spark off innovation diffusion and have long-term impact on adoption-speed and -level. Followers enjoy free-rider benefits but need to handle fierce competition (Parker & Gatignon, 1996). Late entrants face decreasing market potential due to saturation. But competitive dynamics and its driving forces on innovation diffusion are not limited to market *entry*. Market saturation and market *exit* decisions correlate. In the innovation adoption context, market potential explicitly decreases when the ‘S’-curve crosses the point of inflection. In line with the *Industry Lifecycle*, firms leave the market and *shakeout* begins (Gort & Klepper, 1982; Klepper, 2002). We analyze these under-researched endogenous links in our simulation.

In methodical terms, integration of network effects (Rogers, 1976) as well as adopter heterogeneity (Herbert, 2006; Rogers, 2003) are critical model requirements. Providing an advantage over differential equation models, *Agent-based models* are able to handle the complexity of both requirements (Gordon, 2003; Rahmandad & Sterman, 2008). These capabilities are critical factors within innovation diffusion research and make Agent-based modeling a promising venue for developing new diffusion theory (Macy & Willer, 2002; Rand & Rust, 2011; Zenobia et al., 2009). Published models confirm the advance praise and showcase effective ways to combine both requirements in explanatory simulations (Cantono & Silverberg, 2009).

Agent-based modeling became widespread in numerous scientific areas during the last 20 years due to progress in computer hardware and software (Heath et al., 2009). An Agent-based model is a conglomerate of decision-making entities and behavioral rules, simulated in a shared environment

(Bonabeau, 2002). *Autonomous* Agents inspect their current state time step per time step and act based upon predefined behavior rules. Analyses on input/output histories and transitions within the model give insights about micro behavior and macro system results (Zeigler et al., 2005). Simulations contribute to scientific discussions via analysis of emergent and immergent effects (Edmonds, 2010):

- Micro on Macro: How do shifts in individual behavior affect the overall system?
- Macro on Micro: If environmental conditions change, in which way does individual Agent behavior evolve?

Handling of numerous input variables to reconstruct *complex systems* and complex behavior is a key capability of Agent-based models (Edmonds, 2001a; Holland & Miller, 1991). This advantage opens a wide range of applications in several disciplines including Economics, Social Sciences, and Biology. As *Epstein* summarizes, different reasons for Agent-based modeling exist: Prediction is the most important, others include explanation and education (Epstein, 2008). Many published models simulate ‘Homo oeconomicus’ attitudes. *Epstein’s and Axtell’s Sugarscape* model is a famous example in this category (Epstein & Axtell, 1996). Stock market crashes, spread of epidemics, appearances of traffic jams and panic escape behavior are further applications. However, the use of Agent-based models is not limited to human-Agents, as examples in supply chain management, climate change and search engine algorithms prove.

Handling of complexity is a key strength of the Agent-based paradigm, but it is also a major source for errors and critique (Axelrod, 1997; Galán et al., 2009; Leombruni & Richiardi, 2005). An increasing number of variables, rules, and conditions lead to difficulties in *replicability* and *validity*, often described as over-parameterization. Replicability is the ability to re-produce and re-execute models in different frameworks (Rahmandad & Sterman, 2008). It is a fundamental requirement to produce reliable simulation results. *Simplicity* avoids over-parameterization. Modeling approaches based upon simple rules and few configuration parameters are superior in terms of interpretation and replication. They do not necessarily produce simple results. In contrast, simple predictors frequently result in complex behavior, if they are executed in a multi Agent environment. *Axelrod’s KISS* principle (*‘keep it simple, stupid’*) best describes this widely accepted methodology within the scientific community (Axelrod, 1997). “The complexity of agent-based modeling should be in the simulated results, not in the assumptions of the model.” (Axelrod, 1997, p. 6). Validity is a two-dimensional requirement: *Internal* validity focuses on the model’s correctness in terms of simulation (programming) code. *External* validity, a frequent subject and hot topic in literature, targets the matching of simulation configuration with real-world observations (Carley, 1996). Validity in our model comes through the integration of empirical data

and the ‘grounding’ with solid models and theories, like the use of Cournot competition and the *General Bass Model*. External validity is crucial to avoid crude input-output simulations and to build meaningful models for policy analyses.

3.4 The Model

3.4.1 Objective, assumptions, and policy design

Our model’s objective is to simulate innovation adoption within an integrated demand-supply environment that allows an evaluation of policies.¹¹ The underlying demand function links demand and supply in a *multi* Agent-based simulation. The function is determined by learning status (*awareness* for the product) and individual price thresholds (willingness-to-pay) of consumers. Furthermore, the function drives market entry and exit decisions as well as quantity and price. Put simply, diffusion proceeds if interactions distribute awareness (Epidemic effect) and rivalry reduces the market price (Probit effect). Adoption drives supply-side rivalry and vice versa rivalry determines pricing and therefore adoption.

We utilize Cournot theory to calculate competitive dynamics. Cournot competition is a widely accepted economic theory that explains an oligopolistic industry structure in which companies compete on the quantity of output they produce (Besanko et al., 2007). Suppliers share same parameters. This simplifies our model and reduces overall complexity in line with the *KISS* principle. Firms...

- produce a homogeneous product (no differentiation),
- do not cooperate (no collusion),
- have market power (each output decision affects market price),
- define their output quantity simultaneously,
- maximize profits,
- share identical cost structures (variable and fixed costs).

Simulation of policies is crucial since *induced* diffusion is in scope of our analysis. Regulators face different decisions in policy design. Our analysis is guided by four dimensions: *Type*, *targeting*, *timing*, and *scale* of intervention. *Type* defines the kind of policy: Market liberalization, information policies to educate consumers, monetary grants in form of purchase bonuses, or

¹¹ The *NetLogo* code and screenshots are available on <http://www.openabm.org/model/2609>. A video documentation “Policy induced diffusion of innovations” is available online at <http://www.youtube.com/watch?v=9jNTI7TloLM>. Code extracts are listed in the appendix of this paper.

combinations thereof. Eight predefined scenarios measure this dimension (see Table 6). *Targeting* tackles the decision of which target group should be in scope for the issued policy. Anybody? A regional subgroup? Consumers with small income, little spending power, and low probability to adopt? Six different targeting options are included in our model. *Timing* of intervention is the third dimension. Timing includes the *point of time* as well as the *duration* of intervention. *Scale* is the fourth dimension and describes the magnitude: The number of periodically educated consumers within info policies and the size of purchase bonuses within monetary interventions. We leverage sensitivity analyses to measure impacts in the timing and scale dimensions.

Policy outcomes are evaluated in two directions: *Effectiveness* and *efficiency*. Effectiveness is primarily measured via acceleration (adoption-speed) and saturation effects (adoption-level) (Diaz-Rainey, 2009). An effective policy initiates consumers to adopt earlier and/or induces consumers, who would not adopt without the intervention, to adopt. Efficiency measures the trade-off between policy effectiveness and associated costs. For instance, policies may boost adoption-speed and -level remarkably, but generate extraordinary costs. Evaluations include policy costs as well as welfare effects in terms of consumer surplus and supplier surplus.

3.4.2 Structure and procedures

We explain the model's functioning stepwise. Twelve steps sequentially divide the simulation process. The first and last steps bracket a loop that contains the repeated calculations per time-step. These calculations can be classified into three blocks: Demand, supply, and adoption. One loop-repetition represents one simulation period. The loop is performed in an iterative manner until an exit condition is reached. Fig. 14 plots the end-to-end process flowchart in *Unified Modeling Language* (UML).

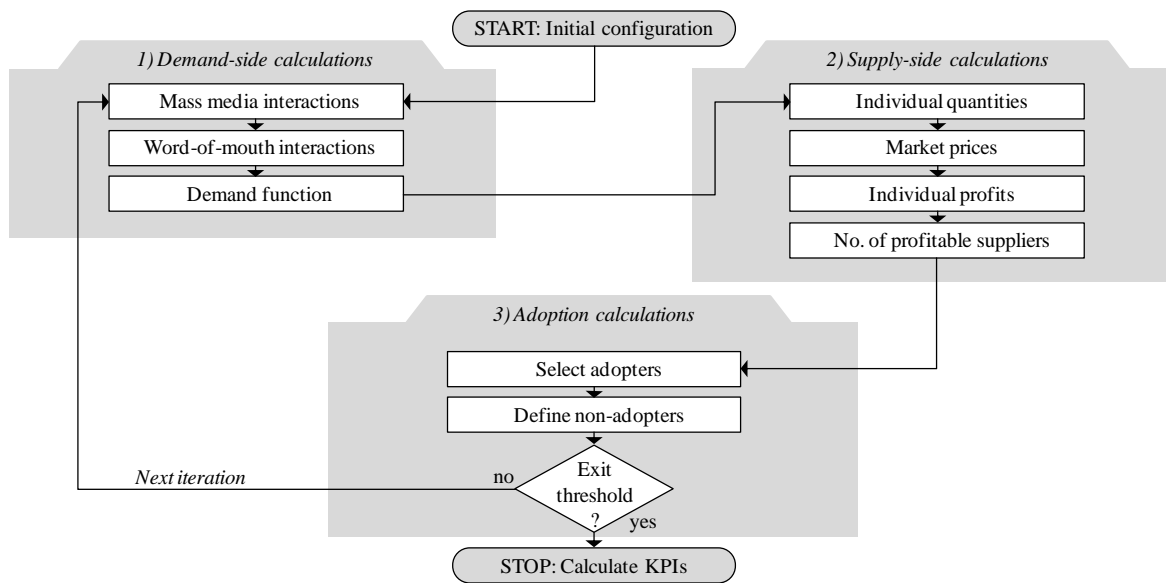


Fig. 14. UML flowchart of model procedures

The simulation starts with initial configurations that populate the ‘World’ with a set of $N = 10,000$ consumer Agents $I = \{ 1, 2, \dots, N \}$ and 20 supplier Agents. *Global constants* and *scenario constants* are calibrated. Global constants remain unchanged across experiments, while the three scenario constants determine our eight predefined scenarios. Table 4 presents all constants and variables. In distinction to constants, *variables* are calculated periodically and drive periodic outcomes, e.g. market price p .

Consumer Agents change their status: At the beginning, all Agents are unaware (subset I_{unaware}). They turn aware if they receive a mass media or word-of-mouth interaction (subset I_{aware}). Innovation gives initial impulses while imitation sparks off widespread diffusion. The *General Bass Model* is applied to empirically validate these communication processes. In line with common coefficient estimates from empirical data, we calibrated a coefficient of innovation (a.k.a. external influence or advertising effect) of 0.03 and a coefficient of imitation (a.k.a. internal influence or word-of-mouth effect) of 0.38 (Mahajan et al., 1995a). The coefficient of imitation is indirectly calibrated through local dispersion measured by the individual number of neighbors $n(i)$ in the Agent’s ‘Small World’. It represents the environment of surrounding Agents to interact with. A screenshot in the appendix visualizes the resulting communication activity (chart ‘Awareness Spread’). If an Agent receives an interaction and turns aware, he decides in the same period whether to adopt (subset I_{adopters}) or not (subset $I_{\text{nonadopters}}$). The decision is driven by the Agent’s individual price sensitivity $z(i)$ and actual market price p . We assume that net income and price sensitivity correlate and use net income distribution from census microdata to empirically validate

$z(i)$ in line with general assumptions of Probit theory and Adopter characteristics (Geroski, 2000; Rogers, 2003).

Table 4. Parameter overview

Parameter	Type	Description	Value	Comment
N	Global const.	Population (no. of consumers)	10,000	
N_{exit}	Global const.	Exit condition (no. of consumers)	1,000	Simulation ends if 90% of consumers are aware
C_{var}	Global const.	Variable costs	30€	
C_{fix}	Global const.	Periodic fixed costs	1,000€	
D	Global const.	Periodic mass media interactions	225	Empirical validation via <i>General Bass Model</i>
$z(i)$	Global const.	Consumer i 's individual price sensitivity	$\mu=1,307€$	According to real-world income distribution
$n(i)$	Global const.	Consumer i 's no. of neighbors	$\mu=5.5$	Empirical validation via <i>General Bass Model</i>
L	Scenario const.	Market liberalization	1 or 0	$L = 0$ if monopolistic; $L = 1$ if liberalized
M	Scenario const.	Additional artificial mass media interactions	0 or 225	$M = 0$ is default; $M = 225$ includes info. policy
G	Scenario const.	Consumer's purchase bonus	0€ or 200€	$G = 0€$ is default; $G = 200€$ includes grant
f	Variable	Demand function with $f=a*p+b$		
a	Variable	Slope-factor of demand function		
b	Variable	Constant-factor of demand function		
q	Variable	Output quantity of each supplier		
p	Variable	Market price		
w	Variable	Supplier's individual profit		
s	Variable	No. of suppliers		

Demand-side calculations: The adoption-loop begins on the consumer-side with a simulation of external (mass media) and internal interactions (word-of-mouth). Spread of awareness is the core driver in Epidemic theory. It assumes diffusion to be sparked off by mass media interactions, followed by epidemic rise in word-of-mouth causing the typical 'S'-shaped curve (see Fig. 13). External and internal interactions trigger the awareness of consumers in our model. Periodically, D consumers are randomly selected and added to subset I_{aware} :

$$I_{\text{aware}}(t, D) = I_{\text{unaware}} \{ 1, 2, \dots, D \} . \quad (6)$$

In case of an active information policy, M -additional consumers turn aware:

$$I_{\text{aware}}(t, M) = I_{\text{unaware}} \{ 1, 2, \dots, M \} . \quad (7)$$

Word-of-mouth interactions trigger awareness through imitation. Adopters of former periods (subset I_{adopters}) interact periodically with one unaware consumer within their 'Small World': These consumers turn aware and are also added to subset I_{aware} :

$$I_{\text{aware}}(t, n) = I_{\text{unaware}} \{ 1, 2, \dots, I_{\text{adopters}} \} \text{ with } n(i) \text{ of } I_{\text{adopters}} > 0 . \quad (8)$$

Altogether, these three subsets define the periodic subset of aware consumers:

$$I_{\text{aware}}(t) = I_{\text{aware}}(t, D) + I_{\text{aware}}(t, M) + I_{\text{aware}}(t, n) . \quad (9)$$

I_{aware} builds the foundation to calculate the eminent demand function f with $f = a * p + b$. First, all Agents are sorted by $z(i)$ in descending order. Second, a linear regression analysis to define slope a and constant b is performed. The y-value is $z(i)$, the x-value is the order position. The following example illustrates the calculation of one period. We assume six aware consumers $\{ z(1), z(2), z(3), z(4), z(5), z(6) \}$ with $z(I_{\text{aware}}) = \{ 100, 80, 60, 40, 20, 0 \}$. Linear regression gives slope $a = -20$ and constant $b = 120$. Demand function equals $f = -20 * p + 120$.

Supply-side calculations: The following steps simulate strategic decision making of suppliers with Cournot linear algebra (Besanko et al., 2007). Suppliers compete in quantities. Demand function f links supply and demand. An essential assumption is ‘Cournot conjecture’: Each supplier aims to maximize profit w based on the expectation that its own output quantity decision will not have an effect on the decisions of its rivals. Suppliers assume their rival’s quantities to be the same as their own quantity and take the quantity of its competitors as a given. Market price p is set at a level such that demand equals the total quantity produced by all suppliers. We begin with the calculation of output quantity q in dependence of the number of suppliers s :

$$q(s) = (b - C_{\text{var}}) / (-a * (s + 1)) . \quad (10)$$

Followed by the calculation of market price p for each q - s -tuple:

$$p(q,s) = a * (q * s) + b . \quad (11)$$

Knowledge of q and p across all possible supplier situations s allows us to calculate individual profits w :

$$w(p,q,s) = ((p(q,s) - C_{\text{var}}) * q(s)) - C_{\text{fix}} . \quad (12)$$

From this point, we know how much profit w each supplier would generate in case s suppliers compete in the market. Strategic decision making implies that competitors enter the market to earn profits. Negative profits ($w < 0$) cause firms to leave. One exception is important: In ‘M’-scenarios with non-liberalized markets, one monopolist serves the market ($s = 1$). Entries are not allowed. In ‘C’-scenarios with competition, as many *profitable* suppliers as possible enter the market: s is increased step by step until another entry would lead to negative profits. We pick up the above example with six aware consumers and assume a monopolistic market with $C_{\text{var}} = 0\text{€}$ and $C_{\text{fix}} = 30\text{€}$. The monopolist maximizes its profits at one half market quantity ($q = 3$):

$$w(1) = ((60 - 0) * 3) - 30 = 150 . \quad (13)$$

Market liberalization would cause two additional competitors to step in:

$$w(2) = ((40 - 0) * 2) - 30 = 50 \text{ and } w(3) = ((30 - 0) * 1.5) - 30 = 15 . \quad (14)$$

Any additional entrant would generate losses: $w(4) = -1.2$. Thus, strategic decision making prevents this rival to enter and s is set to $s = 3$. As the example shows, competitive impact is radical. The evolution from monopoly to duopoly shrinks firm's profits from 150 to 50 and ends up at 15 in the final instance ($s = 3$). The same procedure is applied to calculate exit decisions. Decreasing market potential reduces s and shakeout begins. One assumption includes the order of entry: According to *Klepper's* survival patterns, earlier entrants are assumed to stay longer in the market compared to later entrants (Klepper, 2002). The first mover never leaves the market, because we do not allow to reduce s below $s = 1$. This may result in losses at the very beginning and/or the end of the simulation, when awareness and adoption is too low to cover fixed costs. But innovation diffusion would be impossible if all suppliers exit and nobody sells the innovation.

Adoption calculations: After the final decision on the number of suppliers s , the next step randomly selects the total market quantity of $q * s$ adopters from I_{aware} whose willingness-to-pay is greater than or equal to market price p :

$$I_{\text{adopters}} = \{ 1, 2, \dots, q * s \} \text{ with } z(i) \geq p \text{ and } I_{\text{adopters}} \in I_{\text{aware}} . \quad (15)$$

Residual aware Agents who were *not* selected are added to $I_{\text{nonadopters}}$. Non-adopters are not eligible for further adoptions:

$$I_{\text{nonadopters}} = I_{\text{aware}} - I_{\text{adopters}} . \quad (16)$$

The periodic loop is repeated until the exit condition N_{exit} is reached. While other simulations typically set a maximum simulation runtime as exit condition, we can use awareness as a well-suited exit trigger. The simulation loops until the number of residual consumers is lower than 1,000 consumers: $I_{\text{unaware}} < N_{\text{exit}}$.

The simulation ends with the calculation of key performance indicators (KPIs). KPIs are eminent to evaluate the outcome of each experiment. All KPIs have in common that they are calculated at the final time step when the exit condition becomes active. Table 5 explains our KPIs and how we used them to evaluate experiment outcomes.

Table 5. Key performance indicators

KPI	Description	Calculation	Interpretation
LEVEL	Cum. innovation diffusion after the final time step	I_{adopters} / N	How many consumers adopted?
SPEED	No. of time steps until exit condition is reached	$\text{Max}(t)$	How fast was the adoption procedure?
FIRST	No. of initial competitors ('First Movers') in $t = 0$	$s(t = 0)$	How attractive was the market initially?
MAXSU	Maximum no. of suppliers across all time steps	$\text{Max}(s)$	How intensive was rivalry at the peak?
PRICE	Average adoption price across all adopters	$\sum p / I_{\text{adopters}}$	How intensive was rivalry over the lifecycle?
CPLUS	Consumer surplus of adopters	$\sum (z(i) - p)$	How did consumers profit from the policies?
SPLUS	Supplier surplus (measured as cumulative profits)	$\sum ((p - C_{\text{var}}) * q) - C_{\text{fix}}$	How did supplier(s) profit from the policies?
PCOST	Cumulative policy costs (scenario specific) ^{1,2}	$\sum (I_{\text{adopters}}(t) * G) + (M * 250)$	How much did the issued policies cost?

¹ Monetary grants are accumulated only for adopters who received the grant.

² Assumption: Information policies cause periodic costs of $M * 250\text{€}$. The 250€ are derived as follows: The average market price across all competitive scenarios and across all simulated periods is 828€. We assume a 30% advertising share of total product price which leads to about 250€ in product-related advertising costs.

3.4.3 Simulation execution

We executed the model in *NetLogo*. It is a widely used Agent-based simulation tool. It is very professional in its appearance, documentation and usability and therefore popular among educational users (Railsback et al., 2006). Since random dispersion and random selection of consumers cause contingency effects, we perform numerous iterations to factor-out these contingency effects. Values presented in the results section are arithmetic means across 1,000 repetitions per experiment. Information policies are modeled as additional artificial mass media interactions M that increase awareness. Monetary grants G are modeled as an increase of consumer's price sensitivity $z(i)$. E.g. if Agent i with $z(i) = 1,000\text{€}$ receives a purchase bonus $G = 200\text{€}$, i will adopt at any market price $p \leq 1,200\text{€}$.

3.5 Results

3.5.1 First dimension: Type of intervention

Different intervention-types provide regulators with tools to induce diffusion. Our arsenal covers market liberalization, information policies, and monetary grants across eight predefined scenarios (see Table 6). M and C constitute baselines for monopolistic and competitive market structures.¹² Comparisons between both structures measure liberalization impacts. Fig. 15 and Table 6 present

¹² We refer to a non-liberalized market as monopoly or monopolistic and describe liberalized markets as competition or competitive. However, flexible entry and exit of suppliers may cause liberalized markets to constitute monopolistic market structures if $s = 1$.

results across the eight predefined scenarios. Fig. 15 focuses on the visualization of *periodic* diffusion and its influencers awareness and competition. Table 6 shows *end* results based on our KPIs. LEVEL and SPEED measure policy effectiveness. Efficiency is evaluated by PCOST, CPLUS, and SPLUS. Other KPIs primarily measure competitive dynamics.

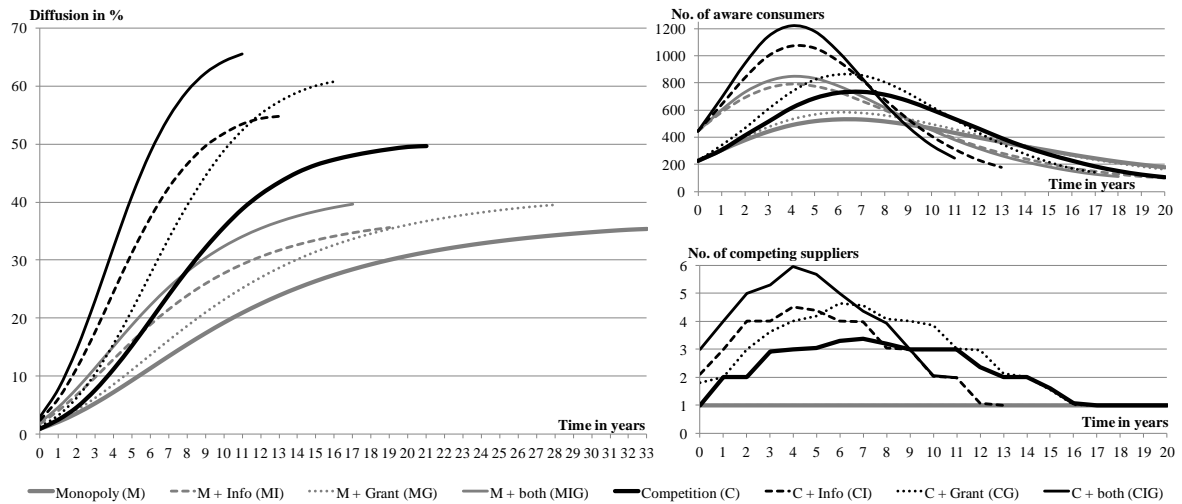


Fig. 15. Cumulative diffusion, awareness, and Industry Lifecycle across the eight predefined scenarios

All eight predefined scenarios show typical ‘S’-shaped diffusion, nevertheless they differ considerably in effectiveness and efficiency. In general, diffusion evolves when mass media kicks off initial awareness of *Innovators* and *Early Adopters* who adopt and cause further spread of awareness through word-of-mouth interactions (network effects). Demand-curve shifts to the right, appealing more suppliers to enter in case of liberalized markets. Monopoly evolves to an oligopoly. Synergies occur: Intensifying rivalry reduces market price p , which increases adoption ratios and in turn awareness. Shakeout begins when the ‘S’-shape proceeds to the point of inflection and demand saturation shifts the demand curve back to the left.

Table 6. Configuration and KPIs across the eight predefined scenarios

Scenario Description	L	M	G	LEVEL in %	SPEED in years	FIRST in firms	MAXSU in firms	PRICE in €	CPLUS in T €	SPLUS in T €	PCOST in T €
M Monopoly baseline	0	0	0	36	33	1.0	1.0	1,194	3,195	1,697	0
MI Info policy in monopoly	0	225	0	36	19	1.0	1.0	1,218	3,210	2,252	1,139
MG Purchase bonus in monopoly	0	0	200	40	29	1.0	1.0	1,304	3,564	2,635	797
MIG Combined policy in monopoly	0	225	200	40	17	1.0	1.0	1,331	3,581	3,088	1,825
C Competition baseline	1	0	0	50	21	1.0	3.6	947	4,763	593	0
CI Info policy in competition	1	225	0	55	13	2.1	4.8	825	5,357	466	762
CG Purchase bonus in competition	1	0	200	61	16	1.8	4.8	871	6,285	547	1,225
CIG Combined policy in competition	1	225	200	65	11	3.0	6.0	766	6,937	348	1,977

Market liberalization: The above mentioned processes showcase *Soberman's and Gatignon's* ideas on supply-demand endogeneity (Soberman & Gatignon, 2005). But they occur only in liberalized markets. A monopolist has no incentive to reduce the price below the profit maximizing monopoly price. Missing rivalry is a burden for consumers. It keeps off price reductions and prevents inclining adoption ratios of consumers. As a result, diffusion proceeds faster and attains higher levels in liberalized markets: M reaches a LEVEL of 36% after 33 years, while C ends up at 50% in a SPEED of 21 years. Furthermore, efficiency ratios measure economic benefits in terms of CPLUS (consumer surplus) and SPLUS (supplier surplus). C results in a 49% higher consumer surplus compared to M and cuts monopolist's surplus by -65%. Overall welfare (CPLUS + SPLUS) exceeds by 9%. We derive proposition P1.

P1: Market liberalization induces diffusion effective and efficiently.

Information policy: The second intervention-type forces suppliers to educate consumers. Scenarios MI and CI map this educational activity through a duplication of periodic awareness interactions. Surprising results occurred. Info policies are partly *ineffective* in monopolies, but highly *effective* in competition: LEVEL keeps unchanged in closed markets, whereas C predicts an increase from 50 to 55%. SPEED increases notably in both market structures, indicating that info policies generally *accelerate* diffusion of innovations. While effectiveness is limited in non-liberalized markets, it is an effective and efficient tool in competition. Awareness shifts the demand curve, appeals more firms to enter, and amplifies rivalry in terms of quantity and price setting. Quicker adoption and higher adoption are striking examples how policy makers may utilize supplier conduct to induce diffusion, described by *Robertson, Gatignon, and Vettas* (Gatignon & Robertson, 1989; Robertson & Gatignon, 1986; Vettas, 1998). The effect is measurable through FIRST and MAXSU. PCOST and welfare KPIs underline the efficiency-boost of such educational stimuli. Consumer surplus rises by 67%, overall economic welfare by 7%. We derive our proposition P2.

P2: Info policies accelerate diffusion efficiently. Diffusion-level increases if info policies induce competition.

Discrepancies between outcomes stress the importance that policy makers need to decide about their primary inducement objective first: SPEED or LEVEL?

Monetary grants: Our 200€-bonus releases its effectiveness in any market structure. SPEED and LEVEL excel the baselines. But mechanisms differ: In an open market, bonuses induce market potential and intensify competition in favor of the consumer. Awareness and adoption interact synergistically. In closed markets, the monopolist skims the higher sales potential and increases market price by half of the consumer's purchase bonus. The monopolist's surplus rises. From a working principle, purchase bonuses increase adoption probability at a given market price, because more aware consumers will accept the price. Real-world examples exist especially among eco-innovations, when purchase bonuses were released as an economic recovery instrument during the financial crises. E.g. as 'Cash-for-Clunkers' programs in the automotive sector.

Generally speaking, a monetary intervention is an effective open market policy but favors primarily the monopolist in a non-liberalized environment. Efficiency depends on the grant's scale. Costs accumulate non-linearly, because bonuses are paid out with each adoption decision. We derive proposition P3. We pick up a discussion on the trade-off between scale and related costs in section 3.5.4.

P3: Monetary grants effectively induce speed and level of diffusion. Efficiency is limited to liberalized markets.

Combined interventions: The primary objective of combinations is to gain synergies between inducements. But these synergies occurred only in liberalized markets. Synergies between rising awareness and intensifying competition induce SPEED and LEVEL stronger compared to all other predefined scenarios. Rivalry is engaged earlier with a higher maximum number of competitors entering the market. Price slumps quickly. Fierce competition cuts supplier profits while consumer profits rise. Overall welfare is highest in this scenario. On the contrary, no synergies occur in MIG. SPEED increases like in MI, whereas LEVEL and PRICE match MG results. The monopolist gains huge surpluses. The duplication of policy costs indicates that a combined intervention is disadvantageous from a benefit-cost-perspective. We derive proposition P4.

P4: Synergies of combined policies are limited to liberalized markets.

3.5.2 Second dimension: Targeting of intervention

Policy makers use targeting to tackle the heterogeneity of adopters and limit interventions to specific subgroups. This 'cherry picking' may reduce policy costs (less recipients) and/or addresses certain adoption barriers (e.g. low income). Simulation results measure impacts in both positive and

negative directions. There is limited potential to increase effectiveness and efficiency, but there is much potential to reduce them with wrong targeting. We identified only one advantageous targeting option per policy. Regulators should apply it carefully. Table 7 explains our six targeting conditions and presents results for competitive markets.

Table 7. Targeting impact in competitive markets

Tar- geting	Consumers ...	Information Policy						Monetary Grant					
		LEVEL delta		SPEED delta		PCOST delta		LEVEL delta		SPEED delta		PCOST delta	
		in %	in %	in years	in %	in T €	in %	in %	in %	in years	in %	in T €	in %
all	without targeting (= CI/CG)	55	0	12.5	0	762	0	61	0	16.2	0	1,225	0
z-	with low willingness- to-pay z(i)	54	-1	13.1	4	793	4	64	5	15.3	-6	681	-44
z+	with high willingness- to-pay z(i)	56	3	12.0	-4	730	-4	49	-19	21.4	32	594	-52
n-	with small no. of neighbors n(i)	55	0	12.4	-1	755	-1	56	-9	18.4	14	601	-51
n+	with large no. of neighbors n(i)	53	-3	15.2	21	912	20	56	-9	18.3	13	594	-51
area	in specific geographical region	52	-5	17.6	40	1,045	37	53	-14	19.7	21	290	-76

Notes:

We measured virtually no difference between market structures. We therefore chose CI and CG results to be displayed in this table.

The 'delta' columns display the *relative* deviation to predefined scenario results CI respectively CG.

Negative SPEED delta values are advantageous (acceleration).

z+ is the only advantageous option with info policies. Targeting of consumers with z(i) *above* average of $\mu = 1,307\text{€}$ results in slight 2-3% improvements across LEVEL, SPEED, and PCOST. This subgroup includes high adoption probability. As more consumers adopt early, awareness spreads faster. Contrariwise, other targeting options—especially a regional focus (area)—slow down circulation of interactions. We derive proposition P5.

P5: Targeting of consumers with high adoption probability and spatial dispersion increase info policy effectiveness and efficiency. Additional execution costs may jeopardize the small benefits in the real-world.

Targeting includes higher saving potentials with monetary grants. PCOST slump as the number of grant-receivers shifts from 6,100 to between 3,400 (z-) and 1,450 (area). But again, only one option increases policy effectiveness: z- tackles consumers with low willingness-to-pay who would not adopt otherwise and induce them to adopt. We derive proposition P6.

P6: Targeting of consumers with low adoption probability increases effectiveness and efficiency of monetary grants.

Both propositions P5 and P6 contradict. Combined interventions face regulators with the challenge to de-couple targeting of both interventions. If this is not possible, they should solely focus on z- targeting: Grant-related z- benefits excel info policy-related z+ benefits. Furthermore, z+ causes strong negative effects applied with monetary grants.

We performed data mining on micro-level characteristics to gain insights on targeting drivers. In line with *Rogers* (Rogers, 2003) and *Mahajan et al.* (Mahajan et al., 1990), we measured adopter heterogeneity through discrepancies in Probit and Epidemic characteristics. Fig. 16 visualizes statistics per adopter category in the C-scenario, explaining why z-options (huge gaps across categories) affect diffusion stronger than n-options (small gaps). Furthermore, the figure displays the empirically validated shift from innovation to imitation.

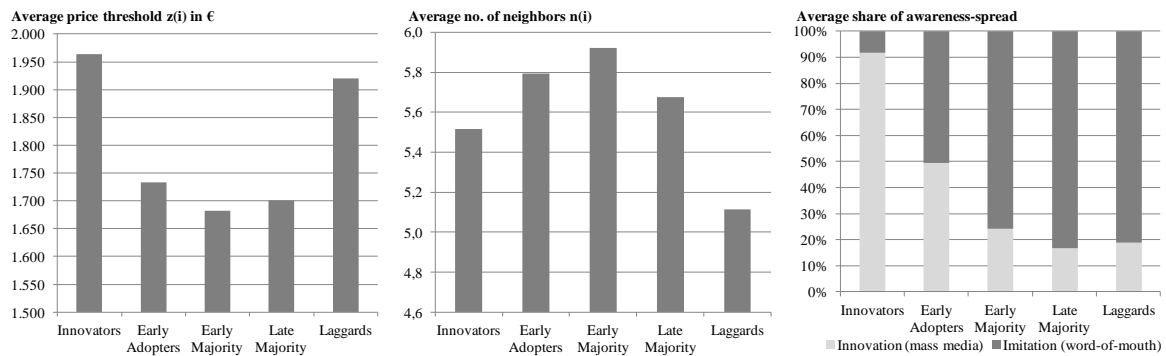


Fig. 16. Adopter characteristics per category in scenario C

3.5.3 Third dimension: Timing of intervention

Policy makers need to decide about policy *start-time* and *duration*. Sensitivity analyses measure clear results across all scenarios: Early interventions are superior in effectiveness and efficiency. Almost linear correlations between start-time and effectiveness ratios exist. On the contrary, duration correlates in a non-linear fashion with LEVEL and SPEED. Small durations increase effectiveness, while long durations are counterproductive in terms of efficiency. LEVEL in the MI-scenario keeps unchanged and is the only exception. We derive propositions P7 and P8.

P7: Early policy start-times increase their effectiveness and efficiency.

P8: Short policy durations increase their efficiency.

Keeping policy costs in mind, lawmakers do best if they intervene early and over a short timeframe. E.g. an info policy issued at the beginning and executed over a period of just ten years

boosts SPEED from 33 to 24 in the MI scenario with a 65% less policy costs. These findings are in line with earlier publications on Epidemic models that stress external influence through mass media to create initial awareness impulses (Mahajan et al., 1990).

Timing is most important in competitive markets and with opening of markets. Inducements gain synergies from more intense competition in case they are released before the Industry Lifecycle reaches its climax. CI, CG, and CIG Industry Lifecycles in Fig. 15 indicate these synergies: Early timing shifts the rivalry-peak to an earlier and higher maximum. These effects are crucial with respect to market liberalization. Late liberalization reduces market potential for entrants. Early liberalization ($t < 9$) engages three or four rivals to compete (measured via MAXSU), whereas late liberalization ($t > 11$) reduces MAXSU to two suppliers.

3.5.4 Fourth dimension: Scale of intervention

Appropriate *scale* is important due to trade-offs between policy costs and policy effectiveness. Small magnitudes are cheaper, but could be ineffective. Large scales might burn money. Predictions differ strikingly between KPIs and confirm our findings from the type-dimension: LEVEL is little (CI) or not (MI) scalable with informational inducements (see Fig. 17; the x-axis is calibrated to predefined scenario configurations. 0% are the default values $M = 225$ and $G = 200\text{€}$). Contrariwise, declining slopes indicate good scalability to trigger SPEED in both market structures. In terms of monetary grants, LEVEL correlate in a linear fashion and with high sensitivity. SPEED-slope is slightly progressive. Taking efficiency into account, regulators face inclining PCOST-slopes for grants and declining slopes with info policies. Policy-related costs are higher in monopolies due to longer execution durations compared to competitive markets. No scalability synergies occurred within combined intervention scenarios. We derive propositions P9 and P10.

P9: Info policy effectiveness and efficiency decrease as intervention-scale increases. Scalability is low. Small-scale info policies efficiently accelerate diffusion.

P10: Monetary grants are highly scalable to induce speed and level of diffusion. Efficiency decreases as intervention-scale increases.

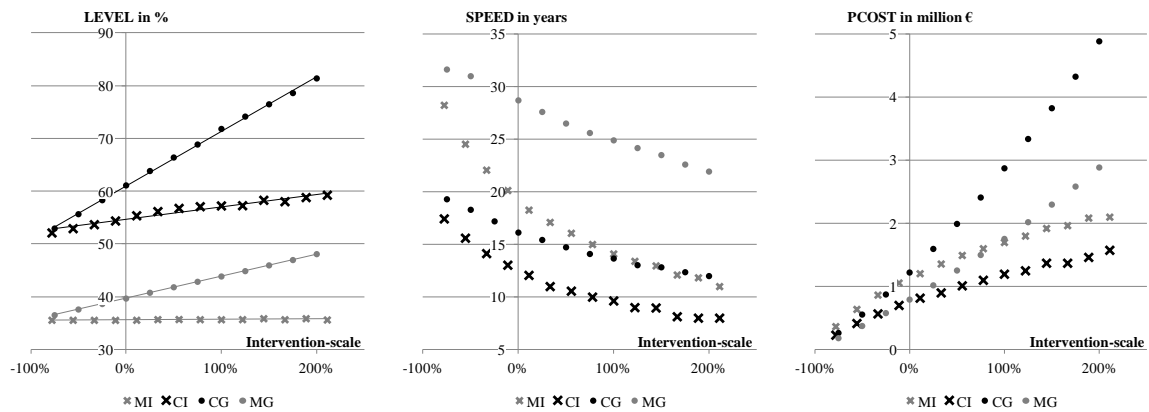


Fig. 17. Scale-sensitivity for LEVEL, SPEED, and PCOST

In sum, SPEED is best induced via educational policies, while LEVEL is best induced by monetary grants. Policy makers should decide on the objective first (SPEED or LEVEL) and then pick best-suited interventions. Authorities can rely on the effectiveness and scalability of monetary inducements. This applies at any stage in the innovation lifecycle, as timing results showed. Rising and upward-sloping PCOST is a trade-off every lawmaker needs to consider. Targeting should be applied to minimize costs and boost efficiency. Monetary grants are the tool of choice to leverage scalability and induce diffusion sharply. But regulators need to take huge surplus imbalances into account in non-competitive markets: Monopolists profit massively from large-scale bonuses.

3.5.5 All dimensions: Forecasting, optimization, and validation of propositions

In this subsection, we *forecast* inducement effectiveness and efficiency *across all four dimensions*. Then, we reuse these forecasts to *optimize* parameter configurations, search for ‘sweet spots’, and *validate* our propositions.

(Agent-based) Simulations excel other methodologies through the ability to perform numerous repetitions with varying parameter settings (Holland & Miller, 1991). Scenario and sensitivity analyses enable lawmakers to test policy configurations in a virtual environment to forecast the success of inducements. E.g. in the context of innovation diffusion, the attainment of politically committed levels within given timeframes. Ongoing target-actual-comparisons and early warnings for deviations help lawmakers during the execution, e.g. to re-evaluate strategies in time. Fig. 18 visualizes LEVEL-PCOST-forecasts in our model. 12,000 configurations factor-in both market structures, timing of liberalization, targeting, start-time, duration, and scale settings. Regulators would design policies by setting a minimum LEVEL and/or SPEED and then select the most efficient configuration setup. PCOST differ notably: In our example, 90% in LEVEL could be

induced with PCOST between 3 and 9.5 million €. Even with massive inducements, adoption-levels in monopolies fall far short of competition.

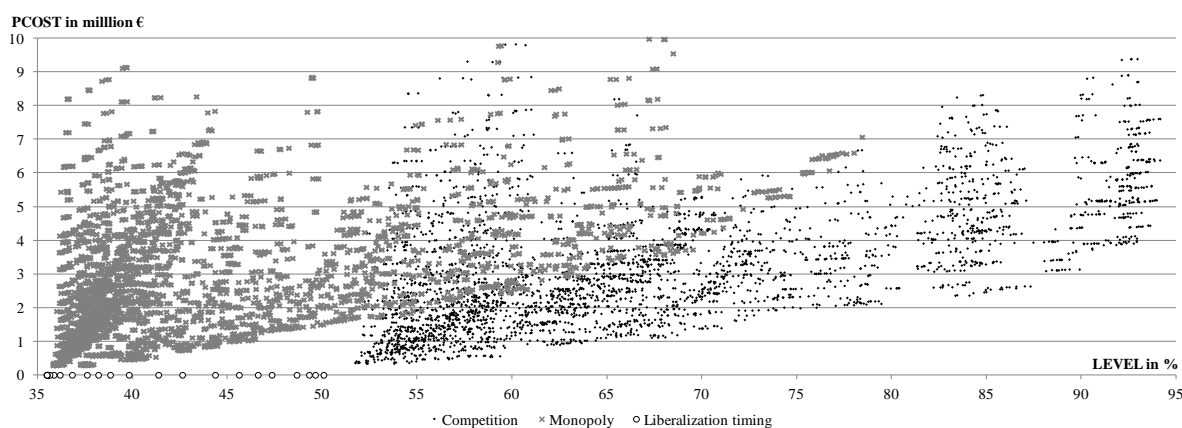


Fig. 18. LEVEL-PCOST-forecasts across all dimensions

We use the same forecasts to optimize policy parameter settings and find ‘sweet spots’. These optimizations need to perform at least as good as the equivalent predefined scenario in LEVEL, SPEED, and PCOST. Results stress four striking findings. First, optimizations for LEVEL and for SPEED show identical configurations. In other words: Optimization for LEVEL is also an optimization for SPEED and vice versa. LEVEL and SPEED interrelate. This is the reason why we group both optimizations in Table 8. Second, statistics predict huge improvements compared to predefined scenarios: PCOST reduces up to -74% (with LEVEL and SPEED capped). LEVEL increases up to 23% (PCOST and SPEED capped). SPEED is accelerated by up to -44% in runtime (PCOST and LEVEL capped). Third, all optimizations use z^- for informational and z^+ for monetary targeting. Start-time is set to the earliest point of time $t = 0$. These settings confirm our findings in dimensions two and three. Fourth, there is no dominant configuration that maximizes both effectiveness *and* efficiency—the latter in terms of PCOST and welfare. Regulators still need to set objectives especially if intervention costs are budgeted.

Table 8. Optimization of policy design for LEVEL, SPEED, and PCOST

Scen.	Optimized for ...	Configuration			Simulation results								
		<i>M</i> index ¹	<i>G</i> in €	Duration in years	LEVEL in %	Δ^2	SPEED in years	Δ	PCOST in T €	Δ	MAXSU in firms	CPLUS in T €	SPLUS in T €
MI	PCOST	720		3	38%	6%	19	0%	540	-53%	1	3,163	2,424
	LEVEL/SPEED	870		5	39%	9%	16	-17%	1,088	-5%	1	3,201	2,662
MG	PCOST		170	16	40%	0%	29	0%	179	-77%	1	3,232	2,256
	LEVEL/SPEED		370	no limit	49%	23%	22	-23%	774	-3%	1	3,605	3,306
MIG	PCOST	750	180	3	40%	0%	17	0%	610	-67%	1	3,166	2,686
	LEVEL/SPEED	970	680	3	51%	28%	10	-42%	1,823	0%	1	4,030	4,214
CI	PCOST	800		1	57%	4%	13	0%	200	-74%	7	5,797	351
	LEVEL/SPEED	760		4	61%	12%	9	-28%	760	0%	7	6,442	250
CG	PCOST		160	no limit	61%	0%	16	0%	502	-59%	4	5,800	563
	LEVEL/SPEED		290	no limit	73%	19%	14	-14%	1,181	-4%	5	7,080	468
CIG	PCOST	580	260	3	65%	0%	9	-17%	825	-58%	7	6,848	279
	LEVEL/SPEED	1230	390	3	75%	15%	6	-44%	1,969	0%	9	8,417	283

Notes:

Late liberalization is not displayed because C results would occur. Configurations include z+ targeting for informational and z- targeting for monetary interventions. Start-time of all interventions is year 0. All optimized configurations must reach a minimum in LEVEL, SPEED, and PCOST of predefined scenario results.

¹ Mass media interactions *M* are measured as the periodic number of consumers to interact with.

² Delta is calculated between the optimization and predefined scenario results. See Table 6 for predefined scenario outcomes.

In a final step, we utilized the optimized configurations from Table 8 to validate our propositions within the boundaries of our model. We assume our ten propositions (derived in isolated dimensions) to be validated, if optimized settings (across dimensions) are in line with these propositions. In sum, six propositions are confirmed, two are only partly confirmed, and two are rejected:

- Comparisons of optimized monopolistic scenarios with its competitive equivalents confirm proposition P1. Liberalized markets excel monopolies in both effectiveness and efficiency. Policy makers should consider market liberalization as a preliminary requirement in advance of any other inducement.
- Proposition P2 is only partly confirmed. Competition is a primary efficiency-driver, but MI shows surprising and contradicting results: A large-scale short-timed informatory policy slightly increases LEVEL to 39%. We conclude that even without competition, info policies may induce diffusion-level.
- Proposition P3 is confirmed. MG and CG show the effectiveness of purchase bonuses, but efficiency is limited to CG. The monopolist is the profiteer in closed markets.
- Proposition P4 is only partly confirmed. No synergies exist in monopolistic markets: MIG is only an accumulation of MI- and MG-inducements. In CIG, the increase in MAXSU indicates synergies, but LEVEL- and PCOST-outcomes reject these indications. Furthermore, too many influencing factors (especially targeting) determine CIG-results to fully validate P4.

- Both targeting propositions P5 and P6 as well as start-time proposition P7 are confirmed, because all optimized scenarios embody corresponding configurations: z^+ respectively z^- targeting and start-times of $t = 0$.
- Proposition P8 is rejected by scenario CG. Short durations do not generally optimize efficiency. CG is optimized through a small scale in combination with a long duration.
- Proposition P9 is rejected. Optimizations indicate scalability (M between 580 and 1,230), but only in combination with short intervention durations. In fact, all relevant optimized scenarios included large-scale info policies.
- Proposition P10 is confirmed. Monetary grants are highly scalable with trade-offs in efficiency. Optimizations show a wide range of configurations (G between 160 and 680€) and outcomes in terms of costs and welfare.

3.5.6 Further scenarios

We analyzed a variety of further scenarios that were not mentioned in the above sections. Objective was to isolate specific drivers, confirm observations, and further validate our findings. The relevance of intensifying competition was tested in *entry barrier scenarios*. Adding fixed entry barrier costs to the C scenario results in less supplier entries and less intensive rivalry. SPEED and LEVEL decrease in line with barrier-magnitudes, until barriers completely prevent suppliers to step in. From this point, output equals M.

Supply-side bonus scenarios evaluated subsidies for suppliers. We reduced variable costs instead of consumer price thresholds. Identical SPEED and LEVEL results as in MG and CG occurred. The modified cost structure leads to price reductions in the same amount as purchase bonuses affect consumer's willingness-to-pay. Suppliers pass their cost advantage to the consumer via lower prices. In the real-world, this is questionable because of 'homo oeconomicus' attitudes and profit maximization strategies.

Low innovation scenarios inspected the impact of Agent heterogeneity on competitive dynamics. We reduced the coefficient of innovation (see section 3.4.2) from 0.03 to 0.01 and less. With many innovations, the coefficient is smaller than 0.01 (Mahajan et al., 1995a). Such configurations led to slower diffusion (as expected), but also to high deviations in competitive dynamics. Surprisingly, MAXSU ranged between one and four suppliers. Without any other changes in parameter settings, one iteration ends up in a highly competitive market with four competitors while the next iteration creates a monopoly. The root-cause is Agent heterogeneity in terms of $z(i)$ and $n(i)$. If random Agent selection of initial mass media interactions chooses consumers with high adoption probability and many neighbors, then diffusion sparks-off. Co-evolution of adoption, awareness,

and demand-curve entices more suppliers to step in. A discussion how suppliers may utilize this supply-demand endogeneity for strategic positioning is included in the following section.

Further *optimization configurations* were tested without the general requirement to perform at least as good as the predefined configuration in *all* three KPIs. For example, we tested which LEVEL can be reached with the same budget in PCOST without SPEED requirements. Optimizations resulted in extreme values for all parameters. E.g. large-scale info policies ($M > 1,500$) with durations of just one year. PCOST was massively reduced by -90% with small-scale but efficiently targeted purchase bonuses. All findings contributed to the proposition-validity-check from section 3.5.5.

We performed *continuously repeated purchases* with varying periodic ratios of consumers, who lose their adoption or non-adoption status and turn unaware again. The underlying idea is that in reality, many innovations are repurchased after a certain timeframe. E.g. cell phones are replaced after 24 months. Main focus of analyses was the Industry Lifecycle. The number of suppliers increased at the beginning, but repurchases prevented market potential to fade away completely. In line with literature (Klepper, 2002), a long-term supply and demand equilibrium evolved without a complete shakeout.

3.6 Discussion

The successful reproduction of adoption drivers confirms Agent-based modeling being a promising methodology for diffusion research in line with literature (Macy & Willer, 2002; Rand & Rust, 2011; Zenobia et al., 2009). We used it to predict implications of inducement stimuli based on effectiveness and efficiency ratios. The Agent-based paradigm is well-suited to combine key diffusion drivers, namely network effects, adopter heterogeneity, and competition. Nevertheless, its explanatory power depends on rigorous implementation of functional requirements. We evaluate the following modeling requirements as critical:

- *KISS*: Simplicity avoids over-parameterization and allows readers to interpret results. Simple micro-level behavior already causes complex and unforeseeable macro-level outcomes (Axelrod, 1997). Our endogeneity findings provide good examples: Without changes in parameter settings, the number and timing of market entries differ per iteration, leading to unforeseeable outcomes. Arithmetic means across numerous iterations are necessary to derive propositions. Many published models fall far short from the *KISS*-requirement. How should readers understand the model's functioning, if its input parameters need to be explained in the appendix, because number and complexity are too high to explain them in the main text?

- *Empirical validation*: Generally speaking, simulations are pre-configured input-output calculations based on *a priori*-defined rules. Input drives output. Garbage-in, garbage-out. Without the validation with empirical data and solid frameworks (e.g. Cournot competition, the *General Bass Model*, and *Rogers adopter categories*), simulations are just conglomerates of assumptions—toys and not tools (Edmonds, 2010). Explanatory power and real-world generalizations are limited.
- *KPIs*: Bottom-up economics and emergent effects are essentially main concerns for Agent-based modelers. Selection, explanation, and tracking of end-to-end KPIs are crucial to understand how micro-level actors cause accumulated outcomes. However, a majority of published innovation diffusion models reduce their results analysis to macro-level metrics—typically the diffusion-level. Our study presents a set of balanced metrics that allow diagnoses from the bottom-up. Welfare ratios (e.g. CPLUS) accumulate impacts of individual adoption decisions. Competition ratios (e.g. MAXSU) measure how individual decisions and Agent heterogeneity change market conditions. In the final instance, high-level diffusion ratios (e.g. LEVEL) consolidate experiment outcomes in contrastable figures.

Our endogenous demand-supply integration is perhaps the most valuable extension of current diffusion research. Published diffusion models typically focus on Epidemic drivers. Changes in price, adoption ratios, and other Probit aspects often base on randomness and are rarely linked to demand-side evolution. We presented a methodical approach to link demand with supply, Epidemic theory with Probit theory, and diffusion research with Industrial Organization. This allows us to define propositions and suggest ideas how policy makers can leverage these links in a co-evolutionary context. Furthermore, we contribute to research issues at the boundaries of market evolution and competitive dynamics (Bayus et al., 2007; Soberman & Gatignon, 2005). Our model is capable to simulate the bi-directional linkage of market evolution and competitive dynamics: Awareness and heterogeneity of consumers drive market potential, which determines supplier conduct. Vice versa, supplier entry/exit decisions and pricing trigger adoption ratios and therefore emergence of market potential. Put simply, supplier have the ability to create their own demand (verifying Vettas (1998)). In the context of commercial launches, they should embed co-evolutionary impulses into competitive strategies: Intensive communication, lead-user targeting, and low pricing lead to quick uptake in sales. Market potential evolves quickly, resulting in economies of scale, lock-in effects, and entry barriers for rivals. But this strategy will appeal many competitors to step in, leading to intensive competition and slump in profits. This makes first movers extraordinary profitable, while followers enjoy free-rider effects, because the innovation is already well-known (Lilien & Yoon, 1990). Contrariwise, firms may choose the opposite strategy

(skimming). They scale communication down and profit from high mark-ups over a long period of time, until market potential slowly evolves and new rivals appear. We measured various impacts of such skimming strategies on supplier and consumer surplus in our model, e.g. in the context of market liberalization (efficient) and monetary grants in monopolies (inefficient). Fig. 19 highlights these findings in relation to order of entry and market structure. It plots a typical profit and survival pattern in the competitive scenario CI as well as average periodic profits across the eight predefined scenarios (see Fig. 15 supplementary). In line with *Klepper's* propositions (Klepper, 1996, 2002), firm survival in our model depends on order of entry: Two first movers earn superior profits. Two followers earn less and survive only a few years. Firm 5 enters during the awareness peak, earns infinitesimal profits, and exits after two years. Policy makers may utilize these constraints to induce diffusion via intensifying competition and to avoid welfare losses by money transfers to a monopolist.

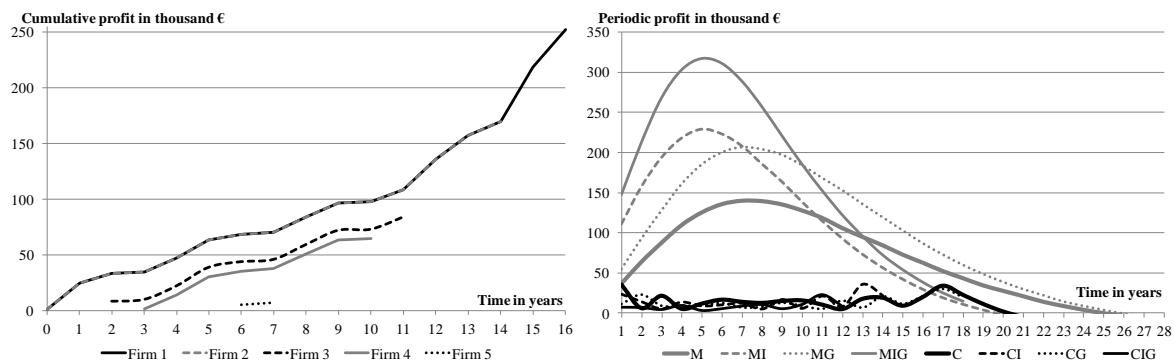


Fig. 19. Survival and profitability in a CI iteration and periodic supplier profits in predefined scenarios

Use of an awareness-driven exit threshold instead of fixed simulation runtimes—as in formerly published models—extends research to diffusion-speed. An important finding is the correlation between *SPEED* and *LEVEL* across all policy types. Any intervention that accelerates diffusion, increases its level—and vice versa. Regardless of this coherence, policy designers need to settle on the overall inducement objective (*SPEED* or *LEVEL*?), because efficiency differs remarkably per stimulus. Market liberalization is effective *and* efficient. We propose regulators to set the stage for competition first and then add other inducements if necessary. Interventions are amplified through demand-supply synergies in competitive markets. Inducements that stimulate rivalry are superior in efficiency. The Industry Lifecycle helps to issue policies in the growth phase of the ‘S’-curve. This is the ideal timing to gain rivalry synergies.

In the real-world, monetary grants are the most likely inducement-option. A typical reason is supply-side lobbying—our measurements on supplier’s surpluses in these scenarios explain why (see Fig. 19). We propose regulators to extend their stimulus-arsenal with information policies. In competitive market structures, they induce diffusion with less costs and risks. However, if monetary grants are required, they should be paid out to consumers directly. Real-world ‘Cash-for-Clunker’ programs are good examples how policy designers can include optimized targeting, timing, and scale to improve policy effectiveness and efficiency. In addition, these programs are typically escorted by awareness-booster due to intensive media coverage.

Policy outcomes present typical ‘S’-curves across all scenarios. Bottom-up analyses confirm both Epidemic and Probit aspects as important adoption drivers. In line with *Geroski’s* roundup (Geroski, 2000), we measured Epidemic awareness-spread to be the primary driver that causes the ‘S’-curve. The attainment of Probit thresholds is secondary, as results in monopolies without price reductions show. Nevertheless, this proportion may change with different innovations. In contrast to other published models, ours is product agnostic and empirically validated by using the *General Bass Model*. The following three ‘Green’ technology examples discuss shifts in Epidemic-Probit-importance and should help policy makers, researchers, and other readers to replicate our model with different configurations:

- *Organic fuel E10*: Diffusion stagnates despite savings for car drivers. Consumers are unsure if their car might suffer damage. Awareness is the primary barrier and negative press boosts resistance. Educational policies are best suited to induce adoption.
- *Electric vehicles*: Media coverage is high. Consumer’s awareness is high. But Probit thresholds constitute adoption barriers. Many countries introduced purchase premiums to induce diffusion. These are best suited to induce adoption.
- *Smart Metering*: Digital online metering is a critical components for intelligent energy networks (‘Smart Grids’). Furthermore, direct consumption feedback reduces energy consumption and contributes to CO2 abatement. Obstacles exist in the form of missing awareness and mismatched Probit thresholds: Innovative energy tariffs are unknown and expensive.

Two limitations restrict the explanatory power of our model. First, use of Cournot competition reduces heterogeneity of suppliers. Competitors incorporate identical cost curves, entry barriers, and competitive strategies. This approach reduces complexity and utilizes a widely accepted economic model. But other publications pointed out the relevance of firm heterogeneity (Herbert, 2006; Klepper, 1996, 2002). Order of entry is one root-cause for heterogeneity. Early movers face different challenges as followers (see Fig. 19). Heterogeneity causes competitive advantages and

determines competitive strategies. Second, consumer adoption processes are simplified in a two-stage awareness/decision-making process. Furthermore, this process is performed only once per Agent. Non-adopters do not turn aware again in later periods. In the real-world, consumers may receive several interactions until they ultimately adopt.

3.7 Conclusion and future research

Epidemic and Probit diffusion theories were combined in an Agent-based model to simulate policy induced innovation adoption. We extended current diffusion research by adding Cournot-based supplier behavior to tackle demand-supply co-evolution showcasing *Soberman's* and *Gatignon's* dependencies between market evolution and competitive dynamics (Soberman & Gatignon, 2005). Scenario and sensitivity analyses identified primary adoption drivers and enabled us to derive ten propositions for effective and efficient policy design. Effectiveness was measured via diffusion-speed and -level, efficiency via cost- and welfare-impacts.

Simulation results underline that one policy does *not* fit in all situations. Market liberalization is a dominant strategy. Intensifying competition is an effective and efficient adoption driver, while closed markets primarily favor the monopolist. Information policies typically accelerate adoption. Monetary grants boost both speed and level. Policy makers must not underestimate synergies across inducements as well as supply and demand endogeneity to keep control over policy costs.

Future research should address our limitations and extend our model with supply-side heterogeneity and *Schumpetrian* dynamics. Creative destruction and leapfrogging could be added by R&D and disruptive innovations (Christensen, 2000; Christensen et al., 1998; Herbert, 2006). Incumbents would need continuous improvements to stay competitive across business cycles and changing consumer requirements (Aaker & Day, 1986; Banbury & Mitchell, 1995). Looking beyond this paper, flexibility of Agent-based modeling allows the tackling of several microeconomic paradigms. For instance, individual cost curves, economies of scale, mergers and acquisitions, competitive strategies, and firm survival patterns.¹³ Agent-based modeling is a powerful toolbox. Nevertheless, modelers need to avoid over-parameterization. Any extension or additional parameter will increase complexity and handicap replicability. *Keep it simple!*

¹³ See (Safarzyńska & van den Bergh, 2010) for a review on demand-supply co-evolution building blocks.

3.8 Appendix

3.8.1 Screenshot of *NetLogo* user interface

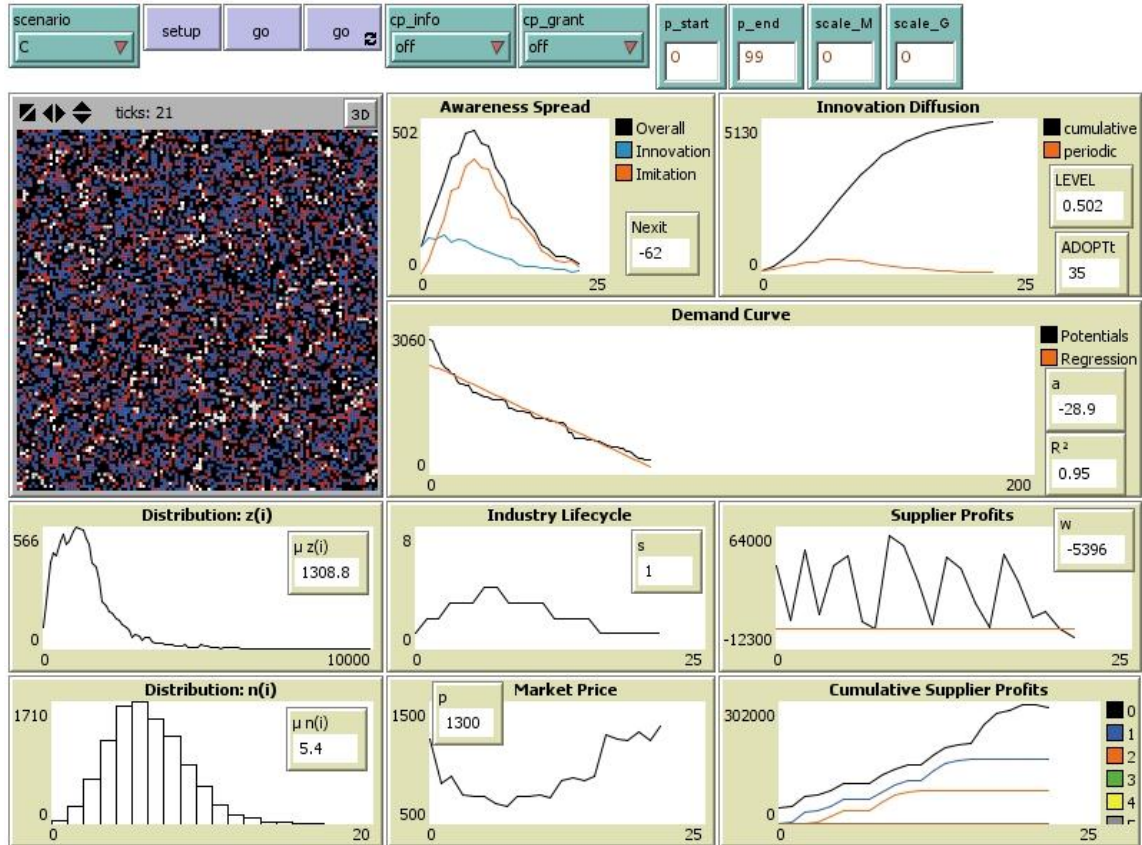


Fig. 20. *NetLogo* user interface showing C-scenario results

3.8.2 *NetLogo* model code

The following *NetLogo* code is an extract of the original code. It displays the awareness-, demand function-, Cournot competition-, and adoption processes. The full code, code documentation, and video documentation are available on: <http://www.openabm.org/model/2609>.

```
;Mass media interactions
```

```
ask n-of D consumers [if color = white [set color yellow]]
```

```
;Word-of-mouth interactions
```

```
ask consumers with [color = blue] [ask n-of 1 consumers-on neighbors [if color = white [set color yellow]]]
```

```

;Calculation of demand function
let data-list sort-by [?1 > ?2] [zi] of consumers with [color = yellow]
let indep-var remove-item 0 (n-values (length data-list + 1) [?])
let matrixvariable matrix:from-column-list (list data-list indep-var)
set b item 0 (item 0 matrix:regress matrixvariable)
set a item 1 (item 0 matrix:regress matrixvariable)

ifelse L = False [set s 1] [;Check if market is liberalized
while [w >= 0] [
  set s s + 1
  let q ((b - Cvar) / ((-1 * a) * (s + 1))) ;Individual output quantities
  set p (b + (a * (q * s))) ;Market price
  set w (((p - Cvar) * q) - Cfix) ;Individual profits
  if s >= 1 AND w < 0 [set s s - 1]
]]

;Select adopters
ask n-of (q * s) consumers with [zi >= p and color = yellow] [
  set color blue
  set CPLUS CPLUS + (zi - p)
]

;Residual aware adopters turn into non-adopters
ask consumers with [color = yellow] [set color red]

```

4. Agent-based Simulation of Consumer Demand for Smart Metering Tariffs¹⁴

4.1 Abstract

An Agent-based model simulates consumer demand for Smart Metering tariffs. It utilizes the *General Bass Model* and *Rogers's* adopter categories to locate demand-side barriers and drivers. Integration of empirical census microdata enables a validated socio-economic background for each consumer. The key performance indicators diffusion-speed and diffusion-level measure the effectiveness of regulatory interventions to induce diffusion. Pricing, promotion, and quantity-regulation policies are tested. Scenario results emphasize the impact of both Epidemic and Probit effects. Speed of adoption is mainly triggered via interactions and consumer awareness. Level of diffusion primarily depends on pricing, willingness-to-pay, and cost-benefit-thresholds. Data mining on Agent's attributes highlight weaknesses in current regulatory requirements due to disadvantages in consumer acceptance and policy effectiveness. A 'cash-for-clunkers'-program could tackle major barriers for adoption and boost diffusion through synergies of pricing and promotion interventions.

4.2 Background

Worldwide, Information- and Communication-Technology revolutionizes the energy supply infrastructure. A surging hunger for energy in combination with an increase in climate protection initiatives pushes the development and usage of 'green' innovations and business models. *Smart Grids* enable load-dependent feed-ins of decentralized electricity sources like photovoltaic and plug-in (hybrid) electric vehicle batteries as well as large-scale power plants like offshore wind-farms and *Desertec* (wik-Consult & FhG Verbund Energie, 2006; World Economic Forum, 2009). A major prerequisite for this revolution and therefore key for sustainable power grids is *Smart Metering* (Brophy Haney et al., 2009; Bundesministerium für Wirtschaft und Technologie, 2007; Kester et al., 2009). An *Advanced Metering Infrastructure* allows frequent measurement processes through Information- and Communication-Technology. Advanced Metering Infrastructure replaces legacy infrastructures with conventional *Ferraris* meters. Electricity, gas, and water consumption

¹⁴ Rixen, M. & Weigand, J. (2012). Agent-based Simulation of Consumer Demand for Smart Metering Tariffs. Unpublished manuscript.

patterns and costs can be visualized in real-time with direct feedback to consumers via in-home displays and online or mobile applications. Bi-directional communication capabilities integrate metering results into grid control, especially for intermittent generators and reserves. Vice versa, households participate in *Demand Response* programs and receive price signals or event-based triggers to control home appliances, e.g. air conditioners, fridges or pool-pumps. Pilot projects successfully prove Advanced Metering Infrastructure's economic and ecologic benefits (European Smart Metering Alliance, 2010). Complexity of benefit drivers rapidly extended during the past years: Having discussed transparency and Demand Response five years ago, we now tackle *Microgrids*, the integration of plug-in (hybrid) electric vehicle charging infrastructure or heat-power-combinations.

Smart Meter diffusion is an example of 'cleaner' innovation diffusion. *Rollout* strategies differ geographically with adoption results ranging from almost zero (e.g. Germany) to nationwide deployments (e.g. Italy). Germany, the Netherlands, and Great Britain are comparable regarding their liberalized energy markets (Pollitt, 2009) and demand-oriented consumer-focused rollout strategy (Vasconcelos, 2008). Rollout strategy choice depends on environmental, technological, regulatory and cultural drivers: "One size does *not* fit all" as the World Economic Forum (2009, p. 3) states. Two approaches exist:

- *Push*: State-aided market push and therefore induced diffusion with focus on large-scale pilot regions (e.g. United States, China, Australia)
- *Pull*: Liberalization of the metering market in order to promote competition and consumer demand (especially Germany, the Netherlands, Great Britain)

A '*Push*'-strategy is typically superior in *speed* and *level* of diffusion due to strict rollout policies. In contrast, the intention of a '*Pull*'-strategy is to promote competition, prevent monopoly prices, and induce innovations (Wissner, 2009). Most important, consumers should actively demand the new technology. Experiences in pilot projects confirm the importance of customer centricity. High consumer acceptance leads to high Demand Response and therefore drives societal benefits (Neenan & Hemphill, 2008). Missing consumer acceptance is a major threat. Customers need to become co-creators of value (Honebein, Cammarano, & Donnelly, 2009). Finally, the choice between a '*Push*'- or '*Pull*'-approach includes a tradeoff between speed and coverage of diffusion on the one hand and expected higher benefits through consumer acceptance on the other.

Objective of this paper is to simulate the diffusion of Smart Metering in Germany in different policy scenarios. An Agent-based model is designed to forecast consumer purchase behaviour and gain insights about adoption barriers and drivers. Results contribute to the discussion, how

Germany's regulator *Bundesnetzagentur* can shape new regulatory frameworks in order to tackle adoption barriers and promote diffusion.

4.3 Literature review

4.3.1 Diffusion of innovations

Innovation diffusion has been an interdisciplinary field of research for more than 60 years. Important contributions came from *Bass* and *Rogers*: In 1969, *Bass* published a common pattern for the adoption of innovations (*Bass*, 1969). It was based upon a generalization of empirical diffusion data for consumer durables, e.g. fridges, TV sets, tumble driers, and air conditioners. The *General Bass Model* describes cumulative adoption of innovations as an 'S'-shaped curve (see Fig. 21). This scheme has been tested and proved in later works (*Bass et al.*, 1994; *Mahajan & Muller*, 1979; *Mahajan et al.*, 1995a) Furthermore, *Bass* offered insights about the shift from mass media communication to word-of-mouth advertising as a primary driver for adoption (see Fig. 21). *Rogers* focused his publications on commonalities and distinctions between adopters. He established five adopter categories (see Fig. 21). They differ primarily in the point of time for adoption, influenced by their use of communication channels, readiness to assume risk, and social affiliation (*Rogers*, 2003). Marketers need to consider implications of both models in order to tap the full market potential of innovations, because market conditions and target groups evolve over time.

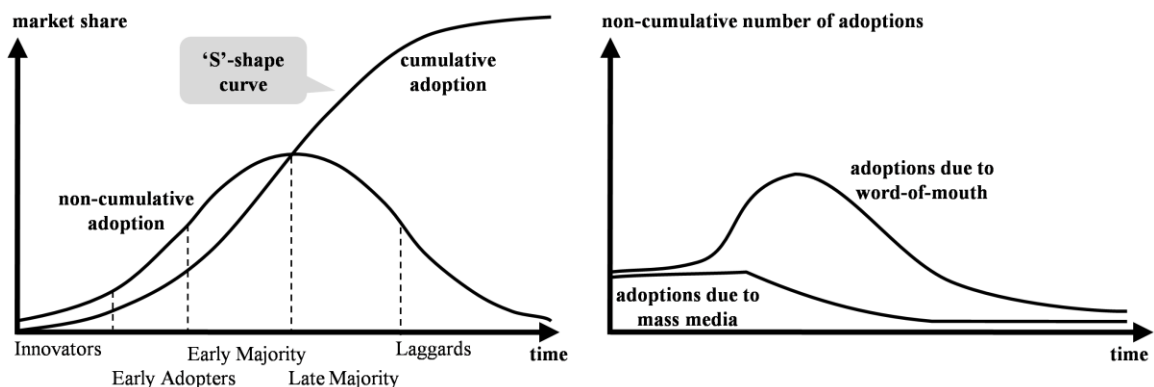


Fig. 21. The *General Bass Model* and *Rogers's* adopter categories (*Mahajan et al.*, 1995a)

Two key performance indicators are suitable to measure the success of market entries: *Speed* and *level* of adoption (*Diaz-Rainey*, 2009). Higher speed results in a steep increase in market share. Consumer durables with short product lifecycles, high risk to be imitated, and/or significant

development effort rely on a fast speed of adoption (Kotler & Bliemel, 2001). A quick attainment of the *critical mass* is crucial. From this point, enough individuals adopted the new product to induce a self-sustaining continued adoption (Rogers, 2003). On the contrary, level is measured by the share of penetration at a given point of time. Some products gain a significant share in the target market, e.g. *Microsoft Windows* in the market for operating systems. While others, e.g. *Linux*, attract only specific target groups and gain only small shares of the market.

Several *influencing factors* drive speed and level of adoption or—in the opposite way—form barriers that avoid demand. Most factors can be identified and explained with *Epidemic* and *Probit* models (Geroski, 2000). Information transmission is the focus in Epidemic models: Awareness drives adoption. The typical ‘S’-shaped curve of cumulative adoption is a result of the multiplication effect of information transmission. When more and more *Innovators* and *Early Adopters* own the new product, interactions rise exponentially and trigger the awareness of residual buyers. Instead, Probit models stress the importance of benefit-cost-thresholds: Economic attractiveness drives adoption. Usually, learning curves and economies of scale determine a reduction in marginal cost per unit over time. Attainment of positive benefit-cost-ratios is necessary to create demand. High perceived net benefits of innovations accelerate their diffusion, while economic risk and technical complexity create significant barriers to postpone the adoption or even cause resistance by potential adopters (Kleijnen et al., 2009).

‘Green’ (or ‘cleaner’, environmental, ecological) technology is a sub-category which gained significance during the past years. Related innovations like Smart Meters are capable to reduce energy consumption, carbon emissions and/or contribute in other ways to a ‘cleaner’ environment. *Montalvo* (2008) gives an overview of related diffusion studies. As *Kemp and Volpi* (2008) summarize, diffusion of such technologies is not instantaneous but follows an ‘S’-shape curve like other innovations. Information transfer, economic attractiveness, and technical complexity impact speed and level of diffusion. ‘Green’ technology diffusion models need to consider exogenous variables like policies, market structures, and communication effects. *Cantono and Silverberg* (2009) describe an exemplary diffusion model that combines policies and learning curves.

4.3.2 Smart Meter diffusion and Agent-based models

‘Green’ innovations research focuses on generation technologies e.g. wind, solar, and biomass (Montalvo & Kemp, 2008). Not surprisingly, Smart Meter diffusion is a scarce subject of analysis since most countries follow a ‘Push’-strategy where adoption is directly induced. In Germany, the Netherlands, and Great Britain, market penetration depends on consumer demand and therefore depends on various social and economic factors that can hardly be calculated. As a result, even

market researchers contain themselves to communicate forecasts.

Zhang and Nuttall handle input factor complexity by the use of an *Agent-based model* (Zhang & Nuttall, 2007, 2008). For several years, social scientists, economists, and researchers from other disciplines use Agent-based models to simulate markets and communities (Heath et al., 2009). Suitable models are capable to reconstruct complex situations and systems with a huge number of variables that affect each other (Edmonds, 2001b; Galán et al., 2009). *Bonabeau* defines Agent-based models as a “{...} collection of autonomous decision-making entities called agents. Each agent individually assesses its situation and makes decisions on the basis of a set of rules. {...}” (Bonabeau, 2002, p. 7280). The Agent-based methodology addresses major complexity challenges in diffusion research and is therefore “{...} a venue for developing new diffusion theory, an area where there has been scant progress for several decades {...}” (Zenobia et al., 2009, p. 339).

In their Agent-based model, *Zhang and Nuttall* calculate intelligent meter adoption through consumer demand based upon behavioral science (Zhang & Nuttall, 2007). They prove the importance of a random lead user selection and benefits of competitive pricing. Their model configuration focuses on interaction (Epidemic) and pricing (Probit). Both publications present typical ‘S’-shape curves and ‘*Lock-In*’ effects—situations in which another tariff or vendor promises a higher perceived value to the user, but no change is performed due to switching costs. The *British Department for Business, Enterprise and Regulatory Reform* released specific policy options which have been tested in the Agent-based model. With regards to requirements from the *EU Energy Services Directive* (European Parliament, 2006), scenarios incorporated the rollout of free in-home displays under different market conditions. Results emphasized substantial impacts of federal grants. Adoption advanced fastest under subsidized conditions with advantages in an open market situation.

4.3.3 Smart Metering in Germany

By mid 2010, there is virtually no relevant demand for Smart Metering tariffs in Germany (Bundesnetzagentur, 2010). Four major *barriers* have been identified in empirical studies. These barriers slow down diffusion, caused by a mix of postponement and resistance. The first obstacle is missing *awareness*. Intelligent meters are as unknown as their potential benefits or available tariffs. The technology is unknown to more than 90% of consumers (Forsa, 2010). Although, informed respondents frequently mentioned chances due to better cost control and consumption monitoring (Donath, 2009).

A second obstacle comes with the *price sensitivity* of consumers related to energy tariffs and associated products. Monetary savings are the primary concern for most respondents, e.g. at least

monthly savings of 10€ are necessary until 50% of consumers would consider a switch to another tariff (Thiemann, Passenberg, & Suer, 2007). Even with great energy conservation and load-shifting effects, it is very difficult to get a positive net benefit with available Smart Meter tariffs. A typical tariff claims installation costs of 80€, additional monthly costs between 8 and 10€ and offers just a small discount of 1 or 2 Cents per kilowatthour (kWh) during off-peak timeframes (Yello Strom, 2010).

In addition to benefit-cost-evaluations, *switching barriers* represent another important obstacle for Smart Meter diffusion. 46% of consumers do not switch their tariff and/or supplier due to comfort reasons, even if benefits overreach costs (Thiemann et al., 2007). Together with perceived risks and low involvement, switching barriers lead to strong '*Lock-In*'-effects and end up in low switching rates of less than 5% per year (Bundesnetzagentur, 2009b).

Data privacy concerns determine the fourth obstacle. Smart Meters collect detailed energy usage data in short intervals of 15 minutes and transfer them to a metering company. Other parties may receive the information as well, e.g. the Distribution Network Operator or the Retailer. With good cause, privacy concerns exists in this context (Deutscher Bundestag, 2009; Karg, 2009). They have the potential to spark-off postponement, resistance, or even opposition. The Netherlands faced this situation in 2009, when Advanced Metering Infrastructure rollouts were stopped due to data privacy concerns (European Smart Metering Alliance, 2010). In Germany, empirical studies proved the significant impact of privacy concerns on consumer attitudes: Almost half of respondents mentioned related feelings as a major concern (Donath, 2009; Forsa, 2010).

4.4 The Model

4.4.1 Consumer adoption process

In this paper, an Agent-based model maps Germany's demand-oriented diffusion approach. Two types of Agents interact with each other: Consumers and suppliers. Suppliers offer a *Smart Meter tariff* to the consumers. The holistic five-step *consumer purchase decision process* of Engel, Blackwell, and Miniard (1995) is utilized to address a variety of demand-side barriers and drivers. The model's step-by-step-approach combines decision-tree and scoring methodologies (see Fig. 22). It combines Epidemic (steps 1, 2, and 5) and Probit effects (steps 3 and 4) to simulate adoption. The appendix includes the programming code (in *NetLogo*) for the consumer purchase decision process.¹⁵

¹⁵ The *NetLogo* code and screenshots are available on <http://www.openabm.org/model/2592>.

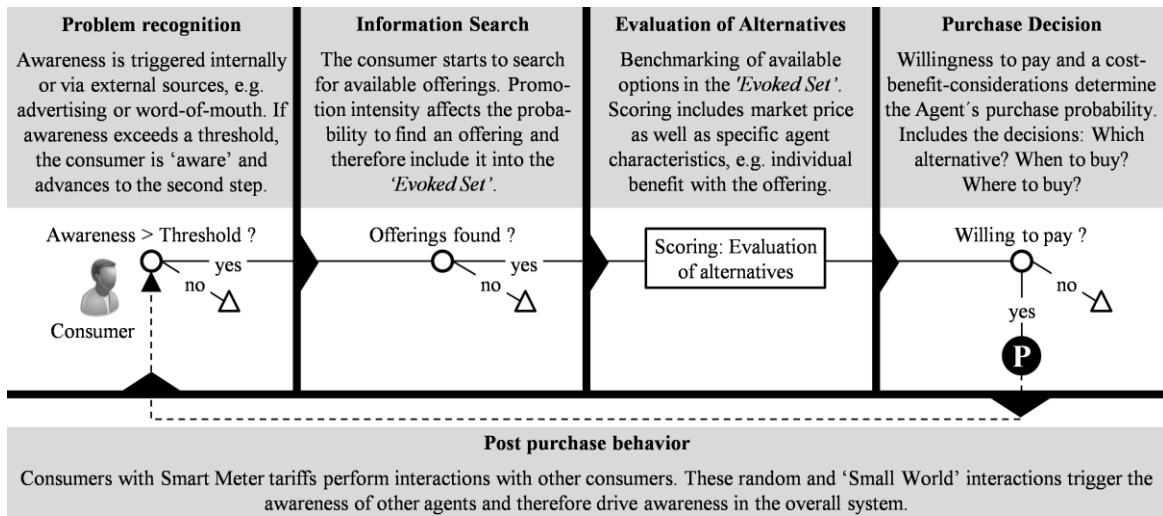


Fig. 22. Five-step consumer purchase decision process (Engel et al., 1995)

Awareness is a basic requirement for Smart Meter diffusion. It is triggered through *interactions* of suppliers and consumers. Suppliers interact through advertising with the use of mass media, consumers interact randomly and in their 'Small World', e.g. family, friends and neighbors. Formula 17 describes Agent i 's probability PI to receive an interaction in period t :

$$PI_{t,i} = (s * A * pi) + (r * B_t) + (w * B_{s,i,t}) . \quad (17)$$

- s probability to receive a supplier interaction
- A number of suppliers
- pi promotion intensity of suppliers
- r probability to receive a random interaction
- B_t number of consumers with a Smart Metering tariff in period t
- w probability to receive an interaction within 'Small World'
- $B_{s,i,t}$ number of Agents with Smart Metering tariff in i 's 'Small World' in period t

Agent i continues to the *information search*, if the number of his interactions exceeds a specific threshold. *Promotion intensity* pi of suppliers (with $0 < pi < 1$) determines the probability to include each supplier in the 'Evoked Set'. Agent i proceeds to the *evaluation of alternatives*, if at least one Smart Meter offering was found. Offerings particularly differentiate in pricing. The simulation calculates monthly costs for the conventional tariff and subtracts expected monthly costs for the Smart Metering tariff (see Formula 18). A positive difference between both options is considered

as Agent i 's monthly net savings potential. Agent i 's expected monthly costs with a Smart Meter tariff M_{sm} consists of fixed and variable pricing components:

$$M_{sm,i} = ((1 - v_i) * C_i * P_{var}) + P_{fix}. \quad (18)$$

v_i Agent i 's electricity conservation potential with Smart Metering

C_i Agent i 's monthly electricity consumption in kWh

P_{var} price per kWh of Smart Meter tariff

P_{fix} monthly fixed price of Smart Meter tariff

In Germany, Smart Meter tariffs typically include higher fixed costs and lower variable prices in contrast to standard tariffs. As a result, large households with high energy consumption profit more from these tariffs (Schäffler, 2010). High monthly net benefits increase the probability for positive *purchase decisions* in the fourth step (see Formula 19). Willingness to pay drives Agent i 's purchase probability PP :

$$PP_i = 0.05 * (M_{st,i} - M_{sm,i}). \quad (19)$$

$M_{st,i}$ Agent i 's monthly costs with a standard tariff

$M_{sm,i}$ Agent i 's monthly costs with a Smart Meter tariff

A calibration with 0.05 as the relevant multiplier maps the 50%-probability to switch the tariff with 10€ in net benefit, which was observed in empirical studies (Thiemann et al., 2007). 50% of households answered that they would switch their tariff in case of a 10€ net benefit. The Agent's status changes in the *post purchase* phase: He is flagged 'smart' and turns from an interaction-receiver to an interaction-sender. He promotes Smart Metering with word-of-mouth activities in random and 'Small World' interactions.

4.4.2 Model calibration and scenarios

Integration of empirical census *microdata* of the German Federal Statistics Office (Statistisches Bundesamt, 2002) ensures realistic assumptions about Agent parameters. The microdata includes empirical study results on the highest level of granularity: Individual statistics or answers per respondent. The appendix contains a programming code for the creation of Agents with the use of

microdata. Each of the 11,500 modeled Agents features an individual socio-demographic background that drives adoption. *Primary microdata attributes* are housing status and the type of boiler installed. Both determine the monthly electricity consumption (Energieagentur NRW, 2006). Primary characteristics immediately influence the purchase decision process, as they drive cost-benefit-evaluations. *Secondary microdata attributes*, e.g. net income, monthly rent, and apartment size represent attributes without direct influence on the purchase decision. Correlation-analyses show interdependencies between both categories, especially household size and net income. Ex-post data mining on adopters gives insight about the ‘average buyer’ in each adopter category.

Tracking of impacts on the macro system (speed and level of diffusion) or on single Agents (arithmetic means of primary and secondary attributes) is key to evaluate barriers, drivers and policy effectiveness.

Different scenarios analyze possible regulatory intervention tendencies. A baseline scenario simulates the current state of the market in 2010. Further scenarios differentiate in pricing, promotion and quantity-regulation. The quantity-regulation scenario reconstructs current requirements of Germany’s regulator *Bundesnetzagentur*: Smart Meters need to be installed in new constructions since 01.01.2010 (Wulf, 2009). Within the model, this policy directly and synthetically increases diffusion through induced purchases.

Table 9. Parameter space in predefined scenarios

Variable	Baseline	Pricing	Promotion	Quantity
Fixprice P_{fix}	18.5€	10...30€	18.5€	18.5€
Promotion intensity pi	35%	35%	0...100%	35%
Induced purchases per timestep	0	0	0	0...10

In the model, Agents are randomly distributed with an average of 40 neighbors (= ‘Small World’) for each Agent. Awareness is set to zero for all Agents at the beginning, representing one major barrier for adoption. All scenarios are simulated over a period of 300 timesteps with a fixed number of three suppliers. Individual energy conservation varies randomly between 5 and 10% per household (Bundesnetzagentur, 2009a). Monthly fixed costs of 10€ are included for the standard tariff. Variable costs per kWh are set to 0.23€/kWh for the standard tariff, the Smart Meter tariff includes 0.21€/kWh.

Apart from the interaction probabilities, the mentioned calibration parameters are adopted from real-world market conditions, empirical study results or census microdata. The following three interaction probabilities represent assumptions and were calibrated through testing cycles in order

to reach full awareness for the technology in the baseline scenario after 300 timesteps (see formula 17):

- $s = 0,5\%$ probability to receive a supplier interaction
- $r = 0,2\%$ probability to receive a random interaction
- $w = 1\%$ probability to receive an interaction within ‘Small World’

4.5 Simulation results and discussion

4.5.1 Overview

The results and discussion section is structured into three parts: We kick-off with a description of macro-level results for the baseline- and intervention-scenarios. Objective is a simulation of the empirically validated baseline diffusion as well as evaluations of intervention-effectiveness in terms of diffusion-speed and diffusion-level. Then, drill-downs on a micro-level allow an isolated view on adoption drivers and how they affect behavior and characteristics of single Agents. For instance, we discuss Agent’s individual price thresholds (willingness-to-pay) in relation to adoption-timing. In a final step, we close the loop between findings on macro- and micro-level and derive implications for efficient policy design. Especially how lead user selections may boost diffusion.

We executed 10,000 iterations for each of the four predefined scenarios (baseline, promotion, pricing, and quantity-regulation) over a duration of 300 simulation timesteps. Like in other Agent-based models, the high number of iterations is necessary to factor-out contingency effects due to random Agent selections. Results statistics in this section represent arithmetic means across these 10,000 iterations. Two global key performance indicators measure the effectiveness of policies on a macro-level:

- *Diffusion-level*: Measures the %-rate of adopters vs. non-adopters after 300 timesteps. E.g. 40% penetration means that after 300 periods, 40% of the consumers purchased the innovation.
- *Diffusion-speed*: Measures how quick adoption proceeds. We use the point of inflection on the ‘S’-shape diffusion curve to calculate speed of adoption. The point of inflection can be tracked via periodic adoptions: The period with the highest number of periodic adoptions is the point of inflection (see Fig. 23 left).

On a micro-level, we utilized Rogers’s five adopter categories (see Fig. 21) to evaluate outcomes, drivers, and barriers. Our microdata validation approach attaches two types of attributes

to each Agent: Primary and secondary attributes. Primary attributes are used during the adoption-decision-process (e.g. electricity consumption). Secondary attributes are not involved in the process, but may correlate to primary attributes due to empirical validation (e.g. household size correlates to electricity consumption). Analyses on both types of attributes per adopter category enabled us to derive specific policy implications on Agent-level. E.g. how pricing policies may address willingness-to-pay barriers.

We extended the execution of the four predefined scenarios with sensitivity analyses. Sensitivity was measured on both macro- and micro-level results. Objective of sensitivity analyses was to evaluate policy efficiency: While diffusion-speed and diffusion-level measure policy effectiveness, sensitivity analyses extend related findings with a view on efficiency. For instance, how do small-scale promotion policies perform in contrast to large-scale interventions? Related findings help policy makers in selecting the most effective type of intervention plus the most efficient magnitude.

4.5.2 Macro-level results and discussion

The *baseline scenario* constitutes a foundational, empirically validated model configuration based upon real-world market conditions. In this scenario, level of adoption reaches 37% after the full runtime of 300 periods (see Fig. 23 *right*). In other words: Without any interventions by the regulator *Bundesnetzagentur*, only 37% of German households will adopt Smart Meter tariffs in the long-run, which falls far short from the targeted 80% by 2020. Interventions are crucial to match politically committed levels.

Baseline results display the general functioning of our Agent-based model in line with *Bass's* Epidemic diffusion model. The cumulative adoption curve shows the typical 'S'-shape development (see Fig. 23 *right*). Supplier interactions (mass media) induce initial adoptions of *Innovators* and *Early Adopters* in the first periods (see Fig. 23 *left*). The 'S'-trend is then caused by an upswing in adopter interactions between the 50th and 150th timestep: Consumer interactions of *Innovators* and *Early Adopters* trigger follow-up purchases of *Early Majority* and *Late Majority* via word-of-mouth. After 125 periods, a maximum of 25 adoptions per period indicate the point of inflection for the diffusion curve (see Fig. 23 *left*). 25 periodic adoptions mean that during one timestep, 25 of the 11,500 households successfully perform the purchase decision process and adopt the innovation. After the point of inflection, the proportion of positive purchase decisions decreases steadily from 25 adoption decisions to 5 purchases in the 300th period. This development indicates the impact of Probit adoption drivers in terms of cost-benefit-considerations: Households with huge benefits adopt Smart Meter tariffs early, while their counterparts with small benefits

frequently decide against adoption. *Laggards* need several purchase decision ‘attempts’ until they finally adopt.

Tackling one key finding of the baseline scenario, we suggest policy makers to include both Epidemic and Probit effects within policy design. Baseline results confirm both rising awareness and willingness-to-pay as influencing factors on diffusion-speed and diffusion-level. Interventions might be ineffective, when focusing primarily on one of the two dimensions only.

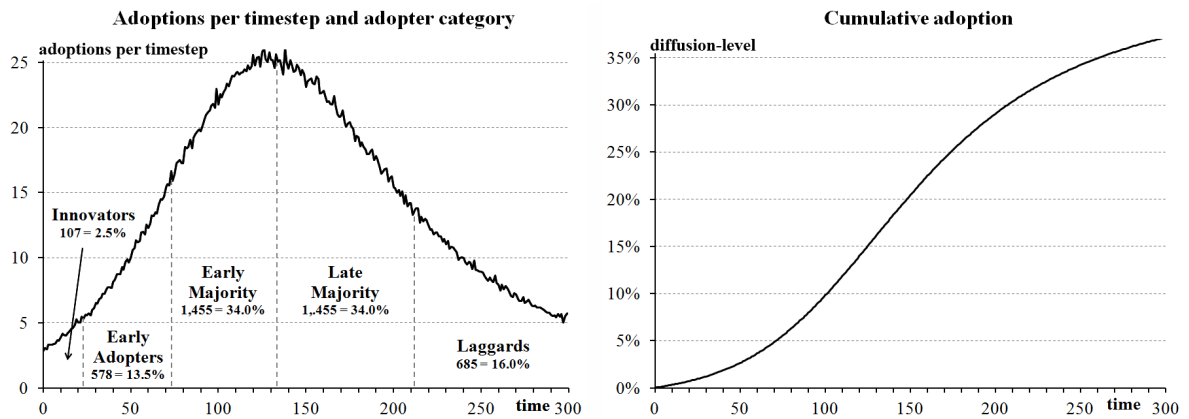


Fig. 23. Smart Meter diffusion in the baseline scenario

Baseline measures indicated substantial Probit impacts on diffusion-level. Due to high Smart Metering tariff costs ($P_{fix} = 18.5\text{€}$), only 37% of households adopted the new tariff in the long-term (baseline). Therefore one major policy option for Germany’s *Bundesnetzagentur* is monetary interventions that improve household’s benefit-cost-ratios. We test this type of intervention within *pricing scenarios*. Basically, we simulate the influence of varying P_{fix} on diffusion-speed and diffusion-level. Fig. 24 (left) visualizes net savings for each of the 11,500 households in ascending order. While 6,000 households suffer losses with the new tariff in the baseline scenario ($P_{fix} = 18.5\text{€}$), a reduction of fixed costs to 17€ decreases this share to 3,500. Agent-based simulations confirm the impact of monetary interventions. Already a small-scale reduction in fixed costs to $P_{fix} = 17\text{€}$ remarkably boosts diffusion-speed and -level: The point of inflection moves from period 125 to period 90, while level rises from 37 to 61% (see Fig. 24 right). Vice versa, increases in fixed costs cause opposite effects and postpone adoption. Overall, we measured high variance especially in diffusion-level in dependence on pricing: Level varies between 5 and 80% in a price-range of $P_{fix} = 21.5\text{€}$ and $P_{fix} = 15.5\text{€}$.

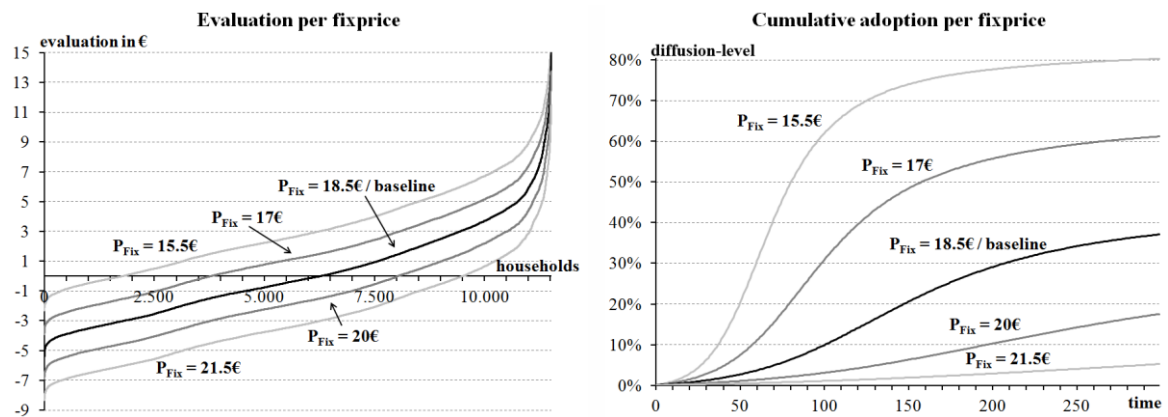


Fig. 24. Smart Meter tariff evaluation and adoption in pricing scenarios

Sensitivity analyses showcase our Agent-based model's capabilities to support lawmakers in efficient policy design. We already know that due to subjections between cost-benefit-evaluations and purchase probability, speed and level of diffusion rise in line with price reductions. Sensitivity analyses enable us to measure exact P_{fix} and diffusion result combinations in the interval from P_{fix} between 10 and 30€ (see Fig. 25). Results show high sensitivity between 14 and 20.5€ with a spread between 95 and 10% in diffusion-level. The point of inflection as performance indicator for speed of diffusion varies between 45 and 230 timesteps. E.g. a monetary intervention that shifts P_{fix} from 18.5€ (baseline) to 14€ would boost diffusion-level from 37 to 95% and speed from 125 (baseline) to 45 timesteps. As a result, the committed 80% at 2020 deadline could be reached.

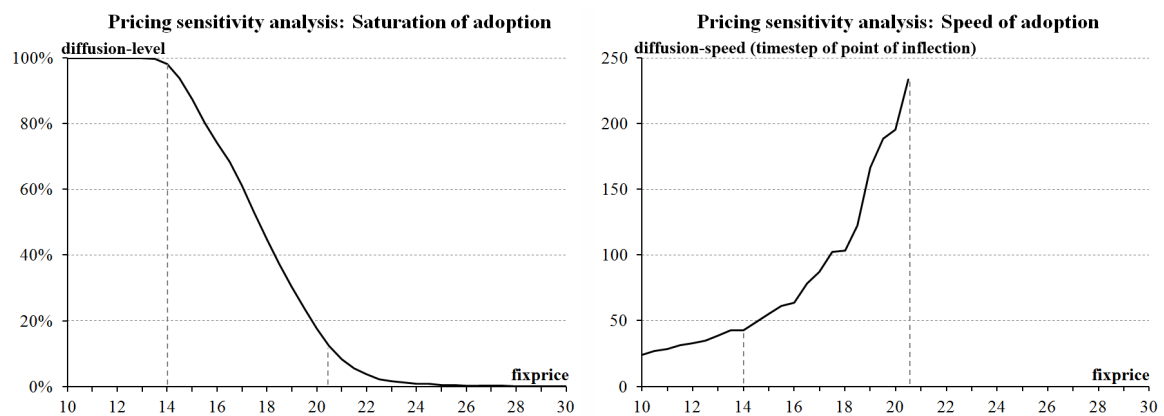


Fig. 25. Sensitivity analyses in pricing scenarios

We suggest policy makers to investigate whether consumer's willingness-to-pay is an important barrier to adoption. In case these Probit price thresholds form barriers (as in our Smart Metering

example), monetary interventions are highly effective methods to induce innovation diffusion. They are also highly efficient if consumers are sensitive to small-scale price changes (as in our Smart Metering example).

Another intervention-type is the informational interventional (a.k.a. education policy). We already stated the importance of external (mass media) and internal (word-of-mouth) interactions in line with the *General Bass Model* and how these interactions drive awareness and adoption. Within the *promotion scenarios*, we simulate artificial increases in external interactions. Focus is on external interactions, because they can be influenced by regulatory directives. In contrast, internal word-of-mouth activity can hardly be influenced by lawmakers. Findings contribute to discussions, if awareness-barriers can be tackled by external information policies and how these inducements impact speed and level of diffusion.

Promotion scenario results confirm the importance of Epidemic effects on diffusion-speed. High promotion intensity effectively induces rapid adoption through a boost in awareness interactions. Fig. 26 visualizes diffusion curves in different promotion intensity scenarios. Three insights can be derived from the results: First, speed of diffusion is clearly accelerated with high promotion intensity. E.g. if promotion intensity is increased from $pi = 35\%$ (baseline) to $pi = 55\%$, the point of inflection moves from 125 to 100 timesteps. Second, in contrast to monetary interventions, informational policies are less scalable due to decreasing efficiency. E.g. a shift from $pi = 75\%$ to $pi = 95\%$ has virtually no effect on diffusion-speed and diffusion-level. Third, diffusion curves with promotion intensity below 35% display the importance of external interactions to initially spark-off awareness (Bass, 1969; Mahajan, Muller, & Bass, 1995b). Speed and level decrease notably.

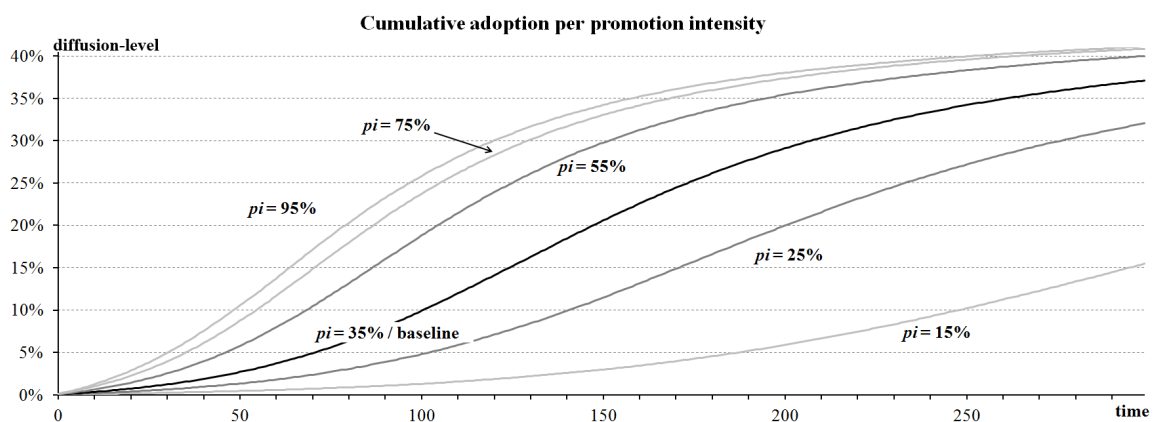


Fig. 26. Smart Meter adoption in promotion scenarios

The third-mentioned finding from Fig. 26 underlines that policy makers need to select the optimal scale of informational intervention. Again, our Agent-based simulation is capable to support scale decisions with the simulation of sensitivity analyses. In order to evaluate the full range of magnitudes, we performed sensitivity analyses between $pi = 0\%$ and $pi = 100\%$. Fig. 27 visualized the results. Level rises quickly until 35% in promotion intensity is reached. Only minor increases in level succeed above this threshold. In contrast, speed reacts different to variations in promotion intensity. Marginal speed of adoption decreases steadily. Slight increases in promotion intensity lead to accelerations in speed of diffusion—especially if overall promotion intensity is low.

Promotion scenario findings showcase the relevance of awareness to speed-up diffusion. We suggest policy makers to investigate whether missing consumer awareness is a critical barrier to adoption (as in our Smart Metering example). In this case, informational interventions form effective and efficient policies to accelerate *speed* of innovation diffusion. However, they might be inefficient to artificially push *level* of diffusion.

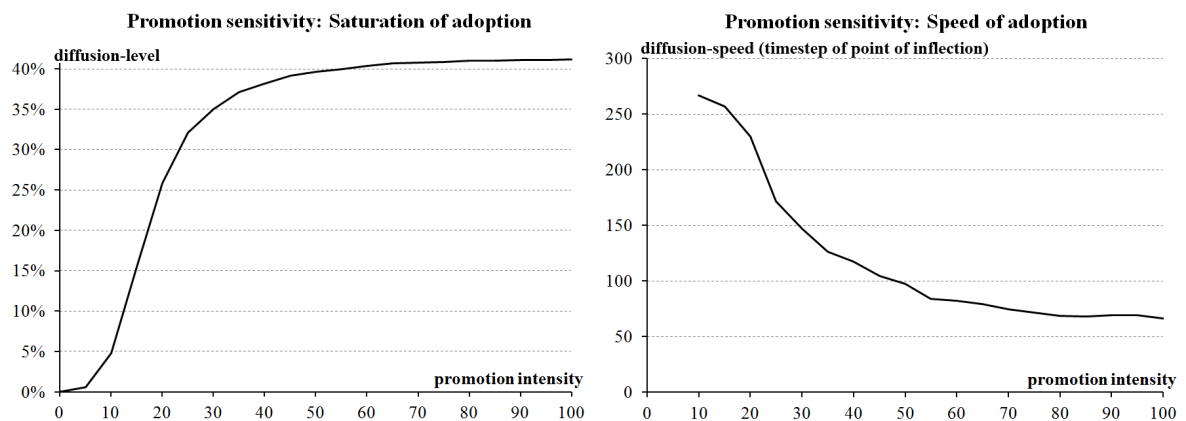


Fig. 27. Sensitivity analyses in promotion scenarios

Our fourth scenario maps the current regulatory framework to induce Smart Meter diffusion in Germany. Since 01.01.2010, the lawmaker requires the installation of Smart Meters in new constructions (Bundesnetzagentur, 2010). The *quantity-regulation scenarios* simulate the outcome of such ‘forced adoptions’. This kind of policy directly and synthetically increases diffusion through induced purchases, skipping both influencing diffusion drivers: Epidemic spread of awareness and Probit willingness-to-pay.

Surprisingly, quantity-regulation effectively increases both speed and level of diffusion (see Fig. 28). Within our preliminary policy design, we expected higher diffusion-level because several

consumers would be forced to adopt apart from negative benefit-cost-ratios. But we expected diffusion-speed to stay unchanged or only slightly increased, because the number of ‘forced adoptions’ is relatively small: E.g. $qr = 1$ means one synthetic periodic adoption, which is relatively small compared to a maximum of about 25 adoptions at the point of inflection (baseline scenario).

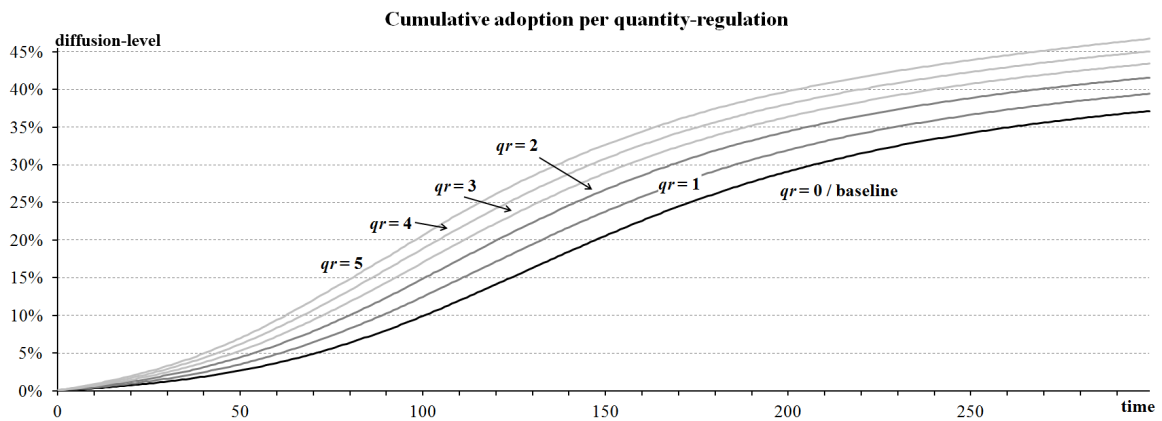


Fig. 28. Smart Meter adoption in quantity-regulation scenarios

Furthermore, sensitivity analyses between $qr = 0$ (baseline) and $qr = 10$ underline the effectiveness of quantity-regulation policies in terms of diffusion-speed. Speed-measures basically display a linear decreasing slope between $qr = 0$ and $qr = 8$ (see Fig. 29 right). This is even more surprising, since the actual diffusion-level shows—as expected *ex-ante*—a declining slope as qr increases (see ‘Penetration’-curve in Fig. 29 left). The declining slope originates from the overlap between ‘voluntary adopters’ and ‘forced adopters’. High qr increases the probability, that a consumer who would have adopted voluntarily during the 300 timesteps, is being forced to adopt. Therefore large-scale regulatory interventions lead to strong reductions in effectiveness (see gap between ‘Actual diffusion-level and ‘Theoretical diffusion-level’ in Fig. 29 left).

We performed deep-dive analyses to identify and isolate the root-cause of the surprising speed-increases. The induced speed results from more internal interaction activity of *Innovators* and *Early Adopters*. Typically, awareness rises slowly due to small numbers of periodic adoptions. E.g. three to five periodic adoptions of *Innovators* induce awareness of other Agents. Even small-scale quantity-regulations are relatively large increases in periodic adoptions during the first periods. Finally, quantity-regulation is a method to indirectly push word-of-mouth interactions.

Besides its ability to induce speed and level of diffusion, quantity-regulation comes along with negative side effects: A certain number of consumers adopted the Smart Meter tariff, although their

individual business case assigns negative benefit-cost-ratios. In other words, these adopters would have never adopted voluntarily. Facing additional monthly costs, opposition can be expected from these adopter groups. In terms of economic welfare, consumer surpluses decline while producer surpluses incline. Policy makers may unintentionally favor skimming strategies of suppliers – especially by monopolists in non-competitive market structures.

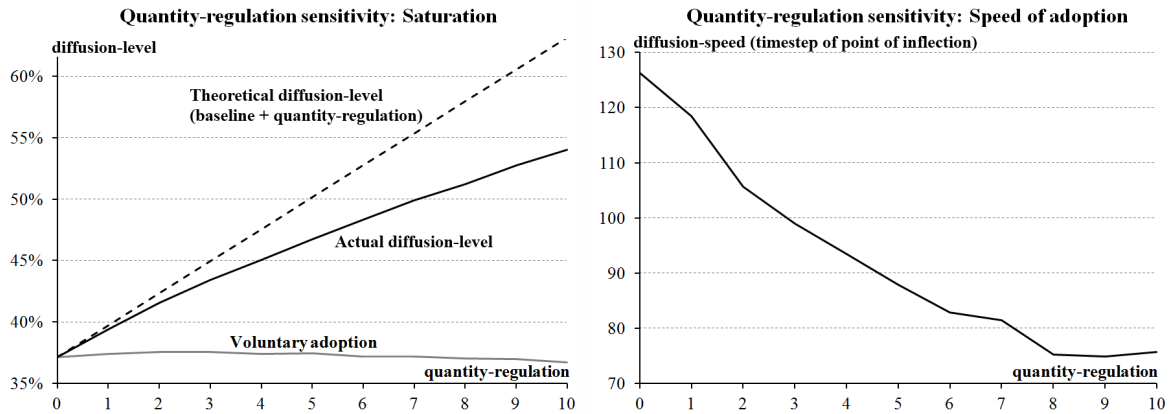


Fig. 29. Sensitivity analyses in quantity-regulation scenarios

We evaluate quantity-regulation in general as well as Germany’s regulatory framework to be very risky. ‘Forced adoptions’ may cause long-term consumer resistance (Kleijnen et al., 2009). Even if diffusion-speed and diffusion-level is possibly induced, other policy options potentially push Smart Meter diffusion more effectively and more efficiently. Pricing and promotion scenarios showcased significantly higher adoption speed and level compared to quantity-regulation.

Table 10. Diffusion-speed and -level in combined scenarios

pi	Diffusion-level: Penetration rate in %					Diffusion-speed: Timestep of point of inflection				
	15.5	17	18.5	20	21.5	15.5	17	18.5	20	21.5
15	75	50	22	7	2	111	162	244	253	183
25	79	58	33	13	4	77	112	163	236	229
35	80	61	37	18	5	62	89	133	195	222
55	81	63	40	21	7	50	69	103	157	189
75	81	63	40	23	8	44	63	96	145	188
95	82	63	40	23	8	44	62	94	158	202

In a final step in terms of predefined scenarios, we tested combinations of pricing and promotion policies. Table 10 visualized the results. No synergies could be measured regarding the diffusion-level. On the contrary, speed of diffusion is further accelerated in combined scenarios compared to

isolated policies. E.g. if fixed price is reduced to 17€ and promotion intensity increases from 35 to 55%, diffusion-level increases only from 61 to 63% compared to a price-only reduction. While the point of inflection, the key performance indicator for diffusion-speed, moves from period 89 to 69 compared to a price-only reduction.

Baseline results displayed the necessity for regulatory interventions and other scenarios presented chances and risks as well as effectiveness and efficiency of concrete policy options. We learned that Probit barriers are of main concern. Pricing policies are best-suited to address these barriers to push Smart Meter diffusion effectively to committed levels. In a final step, we pick up one aspect to optimize the execution of policies in terms of efficiency.

Key concepts in diffusion research include *lead users* and the *critical mass* (Rogers, 2003). Both affect each other: Lead users spark-off Epidemic spread of information throughout the society during the introduction stage. Their influence on diffusion is immense, until a certain number of adopters—the critical mass—is reached. From this point, a reversal of the communication-impact takes place (see Fig. 21): The innovation becomes mainstream and the ‘average adopter’ drives future diffusion. Efficient execution of policies should factor-in lead users and the critical mass to efficiently induce diffusion. E.g. temporary monetary interventions may be executed as purchase bonuses for lead users who spark-off awareness of other households.

Zhang and Nuttall (2007) presented an Agent-based model for Smart Meter diffusion which showcased the importance of lead users with a focus on geographical dispersion. These findings can be confirmed with analyses based upon this Paper’s Agent-based model. Fig. 30 visualizes the Smart Meter diffusion-level within two scenarios: The ‘low dispersion’-scenario limits the consumer-selection for supplier-interactions to a small *geographic area*. As an outcome, diffusion advances faster in the selected area, but slower on a macro-level. It takes longer until the critical mass is reached, with strong negative effects on speed of diffusion. These results match those of *Zhang and Nuttall*. The ‘lead user selection’-scenario switches the consumer-selection for supplier-interactions to a specific *subgroup* of Agents. Households in this group benefit above-average from Smart Meter tariffs and therefore include higher adoption probability. In addition, they have more co-Agents in their ‘Small World’ than the average household. Diffusion statistics present a superior development with improved speed and level. In case they adopt, their internal interactions spreads awareness stronger compared to the ‘average adopter’. Results show that the critical mass is gained quickly through higher periodic purchases during the first 100 timesteps and boosts penetration in comparison to the baseline- and ‘low dispersion’ scenarios. We measured three periodic adoptions (baseline) or even less (low dispersion) without lead user selection and ten and more adoptions

including the selection (see Fig. 30 *left*). In sum, policy makers can leverage lead user selections to increase policy efficiency remarkably across all intervention options.

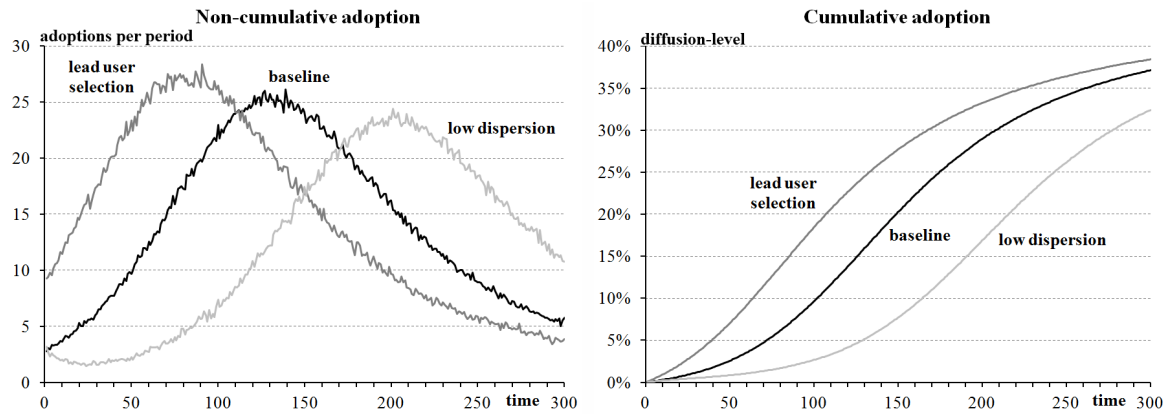


Fig. 30. Adoption within ‘lead user selection’ and ‘low dispersion’ scenarios

4.5.3 Micro-level results and discussion

As a major advantage in contrast to other methodologies, Agent-based models enable detailed analyses on a micro-level. Each Agent includes his own heterogeneous calibration and acts autonomously. In this model, the 11,500 Agent’s socio-economic backgrounds were configured with the use of empirical census microdata. We utilize *Rogers’s* five adopter categories (see Fig. 21) to analyze and interpret adopter characteristics as well as adopter behavior. Data mining gives insight into drivers and barriers for adoption decisions. Comparisons between scenarios, adopter categories, segments, or even single Agents enrich the evaluation process for policy options. In sum, micro-level statistics will help policy makers to better understand the adoption process and will support them in the design of effective and efficient policies.

We split Agent characteristics into two types of attributes: Primary and secondary attributes. *Primary attributes* are directly involved in the adoption-decision-process (see formula 18 in section 4.4.1). E.g. v_i as Agent i ’s electricity conservation potential with Smart Metering and C_i as Agent i ’s monthly electricity consumption in kWh. *Secondary attributes* are not directly involved in the decision-process. But they may correlate to primary attributes and may be helpful to policy makers due to availability of empirical statistics (e.g. net income). Our validation approach leverages census microdata to enable empirical validation among a broad range of different attributes. Typically, census microdata contain hundreds of attributes. Split into primary and secondary attributes ensures one critical Agent-based model requirement: *Keep it simple and stupid!* The Model—respectively the adoption decision process—can be reduced to a few decision variables.

Over-parameterization is avoided, without losing the ability to perform complex data mining across hundreds of (secondary) attributes.

We kick-off our micro-level analyses with comparisons among *Rogers's* five adopter categories. They showcase the impact of Agent heterogeneity and different socio-economic backgrounds. Statistics regarding *primary attributes* present differing Agent characteristics in dependence on the adopter category (and therefore adoption timing). As an example, Fig. 31 visualizes the primary attribute ‘electricity consumption’ per adopter category in the *baseline scenario*. High consumption leads to high Smart Meter tariff benefits and results in higher adoption probability (see formula 19 in section 4.4.1). Statistics show that high adoption probability leads to earlier adoption. These findings are in line with Probit diffusion theory. Decrease in spread (measured in *maximum–minimum* as well as in *upper quartile–lower quartile*) indicates increasing ability of policy makers and suppliers to identify potential adopters within the pool of residual households over time. E.g. laggards may be identified easily in advance, because their primary attributes show small but positive benefit-cost-thresholds.

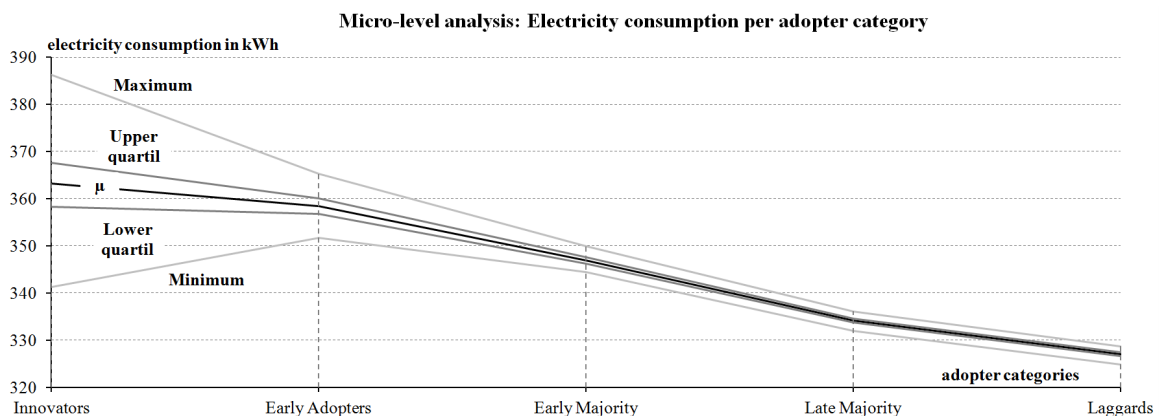


Fig. 31. Average electricity consumption per adopter category (baseline scenario)

Table 11 displays a selection of arithmetic means for attributes in the baseline scenario per adopter category. In addition, the ‘Total’ column shows the total average across all 11,500 households (adopters plus non-adopters). Attribute statistics have two aspects in common: First, arithmetic means decrease over time. Second, all adopter categories have relatively high means compared to the ‘Total’ for all households. The second finding underlines the importance of regulatory interventions to push Smart Meter diffusion in Germany. As we have already seen in macro-results, only 37% of the 11,500 households will voluntarily adopt the new tariffs in the long-term. The 37%-share consists of big households with net income above average, as our micro-level

statistics show. Especially the gap between averages of specific adopter categories and the ‘Total’ stresses the importance of Probit thresholds: Willingness-to-pay and cost-benefit-considerations bracket two specific target groups: Consumers that might adopt over time (whose adoption timing is primarily determined by Epidemic factors) and others who will never successfully complete a purchase process. Effective policies need to tackle these deficits.

Primary attributes vary stronger in terms of standard deviation, due to their immediate integration into the purchase-decision-tree. Influence of both Epidemic (e.g. size of ‘Small World’) and Probit factors (e.g. household size) are noticeable. Secondary attributes are less volatile. While some characteristics stay unchanged, strong correlations to primary variables lead to increasing variations.

Table 11. Arithmetic means for selected Agent attributes in baseline scenario

Attributes	Total average	Innovators	Early Adopters	Early Majority	Late Majority	Laggards
Household size in persons	2.12	3.47	3.43	3.34	3.23	3.16
Cost of standard tariff in €	65.8	93.5	92.4	89.8	86.8	85.2
‘Small World’ size in persons	40.20	40.38	40.40	40.38	40.30	40.24
Net income ¹	10.1	12.3	12.3	12.2	12.1	12.0
Monthly rent in €	317.4	391.4	389.0	386.6	383.5	380.9
Size of apartment in m ²	89.0	106.9	106.7	106.5	105.7	105.1

¹Intervals: 10: 1,700 – 2,000€ per month; 11: 2,000 – 2,300€ per month; 12: 2,300 – 2,600€ per month

As mentioned, regulatory interventions are mandatory to increase the expected 37% diffusion-level to the committed 80% level. We therefore extend the micro-level analyses to the three different intervention scenarios: Pricing, promotion, and quantity-regulation. Table 12 presents results for two important attributes: Electricity consumption (primary attribute) and net income (secondary attribute with strong correlation to purchase probability). Both attributes were selected because initial baseline scenario statistics presented adoption barriers first and foremost in terms of Probit barriers: Negative benefit-cost-thresholds. Any type of intervention needs to address these barriers. The categories *Early Adopters* and *Laggards* were chosen to interpret results because of their similar size (13.5 and 16% of adopters) and their distance in terms of time (almost start vs. final end).

Statistics in the different pricing, promotion, and quantity-regulation scenarios show parallels to macro-level findings: *Pricing policies* shift adopter means remarkably due to Agent’s high sensitivity to price. Significant price reductions shift mean values for *Laggards* (μ of net income = 10.8€) close to the ‘Total’ average (μ of net income = 10.1€). The *promotion scenario* is ineffective with respect to Probit characteristics, confirming that this intervention-type may lead to higher speed but not to higher diffusion-level.

Remarkable findings come from micro-level statistics in the *quantity-regulation* scenario. ‘Forced adoptions’ of households with low electricity consumption and low net income lead to significant conflicts with Germany’s ‘Pull’-strategy: Consumers with negative benefit-cost-ratios are forced to adopt Smart Meter tariffs and face an increase in their monthly bills. The stronger the intervention, the closer declines the mean of values for both categories in the direction of the ‘Total’. In other words: Small households with little net income need to adopt expensive tariffs—consumer surplus is reduced.

Table 12. Arithmetic means for two Agent attributes in different scenarios

Scenario	Electricity consumption in kWh ($\mu = 242.8$)			Net income ¹ ($\mu = 10.1\text{€}$)		
	Early Adopters	Laggards	delta	Early Adopters	Laggards	delta
Pricing						
15.5€	310.0	266.7	-14.0%	11.6	10.8	-7.3%
17€	330.6	290.3	-12.2%	11.9	11.5	-4.2%
18.5€ / baseline	358.6	327.0	-8.8%	12.3	12.1	-1.8%
20€	385.8	363.5	-5.8%	12.5	12.4	-0.6%
21.5€	421.0	408.5	-3.0%	12.5	12.5	0.3%
Promotion						
25%	358.6	333.1	-7.1%	12.3	12.1	-1.3%
35% / baseline	358.6	327.0	-8.8%	12.3	12.1	-1.8%
45%	358.3	324.1	-9.6%	12.3	12.0	-1.6%
55%	358.2	322.8	-9.9%	12.3	12.0	-2.0%
65%	357.7	321.8	-10.1%	12.2	12.0	-2.2%
75%	358.6	321.5	-10.3%	12.2	12.0	-1.9%
Quantity-regulation						
0 / baseline	358.6	327.0	-8.8%	12.3	12.1	-1.8%
2	339.1	315.1	-7.1%	11.8	11.8	0.0%
4	327.3	306.4	-6.4%	11.7	11.6	-0.8%
6	319.4	299.4	-6.3%	11.6	11.4	-0.9%
8	314.3	293.6	-6.6%	11.4	11.3	-1.0%
10	308.7	288.5	-6.6%	11.3	11.2	-1.1%

¹Intervals: 10: 1,700 – 2,000€ per month; 11: 2,000 – 2,300€ per month; 12: 2,300 – 2,600€ per month

4.6 Summary and conclusion

The model in this paper confirmed the capabilities of Agent-based models to simulate innovation adoption behavior and its ability to help policy makers in the design of effective and efficient policies. Especially in ‘Pull’-environments with liberalized market structures, in which autonomous behavior of consumers cause chances and risks. The five-step adoption-decision-process identified both demand-side barriers and drivers. Regulatory interventions were designed, tested, and measured on micro- and macro-levels. Widely accepted concepts were utilized, namely the *General Bass Model* and *Rogers’s* adopter categories. Both Epidemic and Probit effects were observed during the adoption processes. Furthermore, they were verified as major drivers for diffusion.

The integration of census *microdata* to create empirically validated socio-economic backgrounds of Agents opened a wide spectrum of data mining options. While most Agent-based

simulation publications present results only on a macro-level, one key asset of the Agent-based methodology itself is its flexibility on an Agent-level. In this example, consumers were clustered via *Rogers's* generally accepted adopter categories to work out micro-level attribute-statistics. Valuable insights could be transferred into policies and target group selections, especially that Probit thresholds constitute primary adoption barriers and how quantity-regulation may cause consumer resistance.

Baseline scenario results confirm the necessity to issue regulatory interventions. Otherwise committed diffusion-levels will not be reached in Germany. Current quantity-regulation interventions of Germany's regulator *Bundesnetzagentur* might speed-up diffusion in the short-run, but it cannibalizes its own customer-centric '*Pull*'-strategy in the long-term. This is an important finding, since *Bundesnetzagentur* is planning a strong enlargement of this policy on rotational meter replacements (*Bundesnetzagentur*, 2010). While pilot regions (especially *E-Energy*) will give insights about technical questions and user acceptance, main demand-side barriers are not addressed. In particular: Negative benefit-cost-thresholds and missing awareness. Furthermore, low geographical dispersion of pilot regions reduces Epidemic effects and therefore impedes speed and level of diffusion. In any intervention scenario, policy makers need to leverage lead user selections to enable efficiency of applied policies.

Scenario and sensitivity analyses nominate *pricing interventions* as most effective regulatory option, with significant influence on speed and level of diffusion. Consumer's benefit-cost-concerns are addressed, leading to higher adoption-ratios. In addition, current market conditions show *deny-delay-degrade* attitudes (Kurth, 2009) of suppliers—they do not actively promote Smart Meter tariffs. Empirical studies present awareness levels between only 5 and 10% (Donath, 2009; Forsa, 2010). Informational policies could induce widespread education of consumers and are capable to speed-up diffusion effectively, but are ineffective to increase diffusion-level. Two appealing characteristics distinguish educational policies: Lower costs in contrast to pricing policies, e.g. executed as a requirement to educate customers with the next electricity bill. And voluntary adoption decisions as a major difference to installation obligations in quantity-regulation scenarios. An early introduction of informational policies increases their effectiveness due to an earlier attainment of the critical mass.

A 'cash-for-clunkers'-program for old *Ferraris* meters may *combine* pricing and informational interventions. As the president of *Bundesnetzagentur* Kurth (2009) already stated, these kind of purchasing bonuses have the potential to increase awareness significantly, shift benefit-cost-calculations in a positive direction and cause great buy-in of consumers—which might be the most important impact. Acceleration of diffusion would cause synergy effects due to supplier's

economies of scale: Comprehensive rollouts lower installation costs, hardware costs, and operating costs. A quick phase-out of legacy *Ferraris* infrastructure would be possible. With respect to the overall electricity retail market, a ‘cash-for-clunkers’-program could boost supplier-switching rates and therefore intensify competition. Finally, our combined scenario analyses measured no synergies in terms of diffusion-level. Only diffusion-speed may increase. The German regulator should carefully evaluate combined interventions, since its major objective should be increases in diffusion-level to match committed thresholds.

4.7 Limitations and future research

Two limitations reduce the significance of this paper’s model and findings. First, the evaluation during the purchase decision process is limited to monetary ratios. Although savings represent the primary driver, other intentions are capable of inducing demand as well. For example increased cost transparency (Donath, 2009; Forsa, 2010). Second, the simulation focuses on the demand-side with fixed supply-side-behavior. An extension of the model might include competitive strategies in the marketing mix and market entries/exits to fully analyze the impact of liberalized market models. Future diffusion research could copy our combined microdata- and purchase-decision-process-methodology to other situations. For example, driving pattern microdata could be used to identify target groups for plug-in (hybrid) electric vehicles. Or a combination of internet usage, ecological attitude, employment situation, net income, etc. to create product-agnostic innovation diffusion forecast models.

4.8 Appendix

4.8.1 Programming code for the consumer decision process in *NetLogo*

```

;step-1 Problem Recognition and step-5 Post Purchase
;pi promotion intensity
;s probability to receive a supplier interaction
;A number of suppliers
;aw awareness-level (household-specific)
;sm smart meter flag (household-specific)
;r probability to receive a random interaction
;w probability to receive a ‘Small World’ interaction

ask households [

```

```

    if random-float 100 < (pi * s * A) [set aw aw + 1]
if random-float 100 < (count households with [sm = true] * r) [set aw aw + 1]
if random-float 100 < (count households-on neighbors with [sm = true] * w) [set aw aw + 1]
]

;step-2 Information Search
;i temporary variable
;iss information search success (household-specific)

ask households with [aw > 0 and sm = false] [
  repeat A [
    if random-float 100 < pi [set iss true]
  ]
]

;step-3 Evaluation of Alternatives
;b Net benefit/savings potential (household-specific)
;Pfc Fixprice for conventional tariff
;C Electricity consumption (household-specific)
;Pvc Variable price for conventional tariff
;Pfs Fixprice for Smart Meter tariff
;v Electricity conservation (household-specific)
;Pvs Variable price for Smart Meter tariff

ask households with [iss = true and sm = false] [
  set b (Pfc + C * Pvc) - (Pfs + (1 - v) * C * Pvs)
]

;step-4 Purchase Decision
ask households with [iss = true and sm = false] [
  if random-float 20 < b [
    set sm true
  ]
]

```

4.8.2 Programming code for the integration of microdata in *NetLogo*

```
;mc List with microdata
;attAttributes container (household-specific)

set mc [
  [ 1 4 170 43 38 32 6 4 2 2 4 3 1800 ]
  [ 1 6 170 40 30 27 7 7 2 2 4 2 1800 ]
  [ 1 8 0 30 30 140 1 2 2 4 4 1 1800 ]
  [ 1 3 105 26 23 15 6 1 2 2 9 5 1800 ]
  [ 1 4 185 51 9 18 5 4 2 4 3 5 2500 ]
  [ 1 4 135 22 15 12 4 4 2 2 2 5 1800 ]
  [ 1 3 160 45 45 21 6 7 2 4 3 4 2500 ]
  ...
]
set mc shuffle mc

foreach mc [
  create-households 1 [
    set att ?
    setxy random-xcor random-pycor
    ...
  ]
]
```


4.8.3 Screenshot of simulation user interface in *NetLogo*

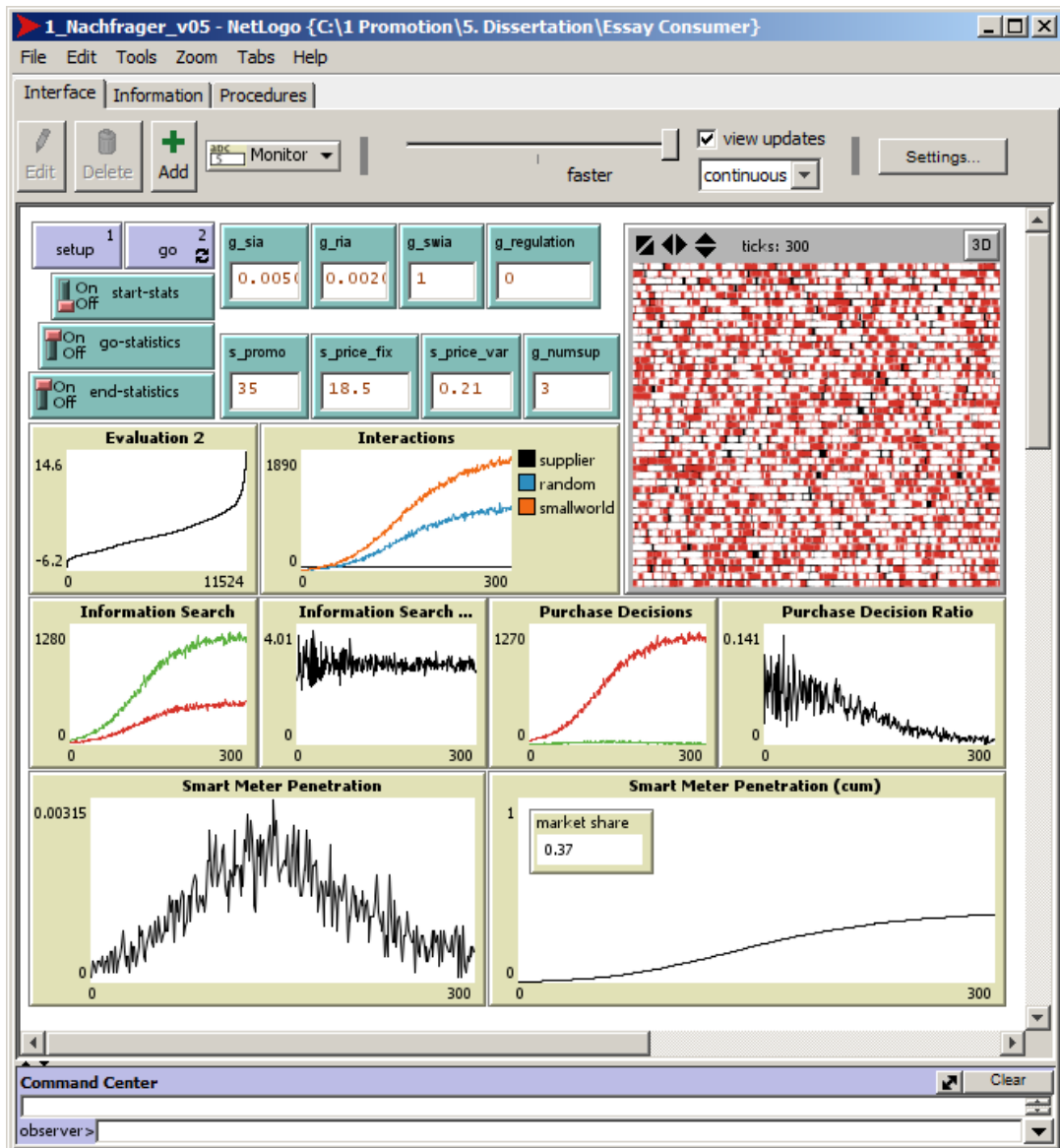


Fig. 32. Screenshot of the Agent-based simulation

5. Conclusion

This doctoral thesis focuses on inducements within the process of innovation diffusion. Chapter 2 outlines fundamental methodical requirements in order to build explanatory and predictive Agent-based models. Comparisons of different validation techniques leads to the maturity matrix—a holistic framework that helps in matching functional model requirements with feasible external validation taxonomies. Finally, the best-suited validation approach depends on the model's objective and the available empirical data. Researchers should clearly state the model's purpose, how and why they validated each input factor, and how validation affected the outcome. Results from Chapter 2 determine validation approach and critical model requirements for programming an Agent-based model that simulates the diffusion of innovations. Requirements differ remarkably between explanatory and predictive model purposes, as the innovation diffusion example concludes.

Chapter 3 contributes to current diffusion research through policy simulations for adoption inducements. The underlying Agent-based model is an extension of the example from Chapter 2. It combines Epidemic and Probit diffusion theories in an Agent-based model and adds Cournot-based supplier behavior to tackle demand-supply co-evolution. A major research contribution from Chapter 3 comes with the confirmation of *Soberman's and Gatignon's* dependencies between market evolution and competitive dynamics (Soberman & Gatignon, 2005). These dependencies drive market liberalization results remarkably and make market liberalization is a dominant strategy for regulators. Simulation results underline that one policy does *not* fit in all situations. Intensifying competition is an effective and efficient adoption driver, while closed markets primarily favor the monopolist. Information policies typically accelerate adoption. Monetary grants boost both speed and level. Policy makers must not underestimate synergies across inducements as well as supply and demand endogeneity to keep control over policy costs.

In Chapter 4, the Agent-based model is further specified in order to map the German Smart Metering market. Special focus is on consumer demand, because of the market driven '*Pull*'-approach to rollout Smart Meters of Germany's regulator *Bundesnetzagentur*. A five-step adoption-decision-process is therefore introduced into the model. Furthermore, a variety of real-world data configure model parameters in line with validation requirements from the maturity matrix in Chapter 2: Tariff information, supplier's marketing mixes, and purchase probabilities of households. First and foremost, simulation results confirm the necessity to issue regulatory interventions for a comprehensive diffusion of Smart Metering tariffs. Induced diffusion is required

to attain politically committed deadlines. Scenario and sensitivity analyses nominate *pricing interventions* as most effective regulatory option, with strong influence on speed and level of diffusion. Consumer's benefit-cost-concerns are addressed, leading to higher adoption-ratios. Informational policies could induce widespread education of consumers and are capable to speed-up diffusion effectively, but are ineffective to increase diffusion-level. A 'cash-for-clunkers'-program for old *Ferraris* meters may combine benefits from both pricing and informational interventions.

Overall, induced diffusion of innovations is under-researched and will gain significance in the next years, particularly in the context of 'Green' technologies. This doctoral thesis explains fundamental diffusion theories and their impact on inducements. Simulation results stress the preliminary assumption, that different policy options induce adoption through different drivers. Informational policies stimulate Epidemic procedures. Monetary grants tackle cost-benefit-thresholds of Probit theory. Solid models are required to simulate policy effects in the context of certain innovations—the Smart Metering example in this thesis is just one example of upcoming 'Green' technologies. Methodical findings contribute to this requirement and guides researchers how solidity can be enabled in Agent-based diffusion models.

Future induced innovation diffusion research should re-use the models programmed for this doctoral thesis. Replication would further confirm the applicability of Agent-based modeling in diffusion research. The product-agnostic model from Chapter 3 is the best starting point.

The German regulator *Bundesnetzagentur* should re-evaluate its Smart Metering diffusion strategy and verify adoption actuals (typically outlined in the yearly *Monitoringbericht*) with prognoses from Chapter 4. Regulatory interventions will be required to fulfill diffusion objectives. Otherwise, supplier *deny-delay-degrade* attitudes (Kurth, 2009) and consumer adoption barriers will prevent Smart Meters to diffuse.

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According to § 10 No. 7 of the Doctoral Studies’ Guide Lines
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