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The Role of Uncertainty for Product Announcement Strategies: The Case of Autonomous Vehicles

by

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Abstract: We study how uncertainty about performance and safety of autonomous vehicles (AV) influences the success of two prototypical strategies governing the producers' timing of the release of new models. Producers can announce the date of the next market introduction or commit to a minimum quality level. Consumers might opt to purchase a new AV, delay the purchasing decision, or resort to purchasing a conventional vehicle. Relying on a calibrated agent-based simulation model, we show that committing on the quality level of the new release yields a competitive advantage and investigate how the degree of uncertainty and consumer attitude toward uncertainty influence the relative performance of strategies and market diffusion of AVs.

Keywords: New product introduction; announcement strategy; uncertainty; autonomous vehicles; agent-based modeling and simulation

JEL classification code: C63, D81, L62, O33

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1 Introduction

Product, price, place, and promotion—also known as the '4 Ps' determining the so-called marketing mix (e.g., Kotler and Keller, 2006)—refer to key considerations when introducing a new product into the market. Obviously, the corresponding decisions are of high relevance for marketers given the substantial cost that is associated with launching a new product (e.g., a double-digit million euro figure for the market introduction of a new car model[1]). Moreover, consumers typically do not honor product generations in rapid succession as they are not willing to repurchase a product each time a new version hits the market. Thus, when the opportunity arises, managers need to "get it right" at their first attempt.

In the work at hand, we address a facet of the latter 'P' from the marketing mix (i.e., promotion) as we are interested in the success of certain firm strategies for announcing the future availability of new products in markets for which the respective technological progress is uncertain at the time of these announcements. Both, the firms' strategies and the corresponding behavior of prospective customers, add complexity to innovation diffusion in such markets. Therefore, decision makers need to take consumers' forward-looking utility expectations and individual needs as well attitude toward uncertainty into account when designing a proper announcement strategy as part of their product launching endeavor.

Autonomous vehicles (AVs)[2] constitute a prime example for a market in which such uncertainties may play a decisive role. Obviously, advanced AVs can improve the productivity of the time spent in cars and they potentially increase the safety and efficiency of the transportation system. Correspondingly, the AV market size is projected to reach over 2.3 trillion US dollars in 2030 (Statista, 2023). However, it is difficult to precisely predict the functionality of future AVs (e.g., with respect to limitations of their self-driving modes regarding maximum speed or long distances) due to remaining technological challenges (e.g., related to environment detection, pedestrian detection, path planning, motion control, and vehicle cybersecurity; see Martinez-Diaz and Soriguera, 2018; Parekh et al., 2022) or legal issues (e.g., regarding liability; see Dawid and Muehlheusser, 2022).

This uncertainty on the side of the producers makes it particularly difficult for them to commit to a strategy for announcing the next generation of their products. Inspired by the work of Lobel et al. (2016), we investigate two al-

[1] Estimate was communicated by a senior manager from the automobile industry. However, this costs are still comparatively low compared with development costs, which may pile up to a billion euro for a new car series.

[2] SAE (2021) distinguishes between six level of autonomy of AVs ranging from "SAE Level 0", in which cars only provide warnings and momentary assistance, to "SAE Level 5", in which fully autonomous driving is possible under all conditions. As of today, most AVs can reach level 2, for which constant supervision by a human driver is required by law, while a few AV models of level 3 are approved for use on public roads in certain countries. For the purpose of our research, we consider cars from level 3 onwards as AVs.

ternative strategies to do so.[3] In the first alternative ("time strategy"), a firm commits itself to a time schedule for introducing the next product generation into market (e.g., the next generation is presented regularly at a certain fair such as the Shanghai Auto Show or at a similar event). In the second alternative ("quality strategy"), a firm does not announce a concrete date for the market introduction of the next product generation in advance but promises to release new product versions cyclically with a constant level of technology improvement.

Model-wise, the game-theoretic approach by Lobel et al. disregards a couple of factors that play a role in adoption processes of real customers, particularly so when it comes to high-priced durable and prestigious products that are used on a regular basis and potentially might even be life-threatening (or life-saving), such as in the case of AVs. These factors include (i) the shape of technological progress (modeled through technological s-curves), (ii) heterogeneity of customers with respect to their preferences, communication behavior, or their attitude toward uncertainty, (iii) individual decision-making (purchasing) behavior, and (iv) interactions with peers (e.g., through word-of-mouth). When properly accounting for these factors, we have to deal with a complex system that is inherently intricate, involves stochastic elements, and is predisposed to emergent—and sometimes unexpected—outcomes. Consequently, agent-based modeling (ABM) comes into play as it often is "the only game in town to (appropriately) deal with such situations" (Bonabeau 2002, p. 7287).

After having set up an agent-based market model and performing extensive simulation experiments, the research contribution of our work is twofold: First, we analyze the effects of applying the two distinct firm strategies for announcing the next generation of AVs. Our results also illustrate that taking into account the above-mentioned influence factors play a role. It is noteworthy that the calibration of our simulation runs is based on data from a representative study on behavioral intentions of consumers in Germany regarding the (hypothetical) purchase of AVs. Second, we focused on consumers' attitudes toward dealing with uncertainty and performed additional simulation experiments. The results from this additional simulation study show that consideration of different attitudes toward uncertainty matters. Thus, we open up a novel (sub-) field of research to be considered by colleagues in their future work when it comes to the adoption of (radically) new products in which uncertainty plays a significant role.

The remainder of this work is organized in the following manner. In Section 2, we provide a more in-depth overview on existing literature on AV development, launching strategies, ABM of innovation diffusion, and corresponding specifics regarding the information transmission in such simulations with respect to social networks and word-of-mouth communication. In Section 3, our agent-based

[3] Lobel et al. (2016) study non-specific product categories (although referring to Apple's iPhone as a motivational application case). In their first setting ("on the run"), no announcement takes place, while in the second setting ("two-cylce"), firms commit to a schedule of technology release for which a small technology increment is followed by a larger one.

market model is introduced. Section 4 presents results from the empirical study that has been used for calibrating the AV market simulation. Section 5 offers results from a first set of simulation experiments, in which we compared the two announcement strategies when being employed by competing firms and analyzed the effect of technology curves as well as the effect or consumer heterogeneity. Section 6 is concerned with results that were obtained when also investigating the effects of different attitudes toward uncertainty. Finally, Section 7 concludes this work and provides an outlook to promising directions for further research.

2 Background

2.1 Economic Aspects of AV Diffusion

The potential gains and also the challenges associated with the development and diffusion of AVs have attracted considerable attention in different fields of literature. A common denominator in much of this literature is the substantial role of different types of uncertainty (technological, economic, legal) arising in the context of AVs. In that respect it has been argued that the large uncertainty facing both producers and consumers might be an inhibiting factor for the market penetration of AVs (see, e.g., Fagnant and Kockelman, 2015) and the importance of direct experience by consumers has been stressed (Hancock, Nourbakhsh, and Stewart, 2019).

A large stream of literature has focused from a purely technical perspective on the development of models and methods for controlling AVs (see Di and Shi, 2021, for a recent survey) for tasks like overtaking, lane changing, merging, or similar. Uncertainty of the traffic environment is a factor to be accounted for in these frameworks, but also the reduction of the uncertainty associated with the behavior of an AV controlled by (AI-based) algorithms, relying, e.g., on reinforcement learning approaches, is an important issue (see, e.g., Bouton et al., 2018). From a more economic perspective, a number of theoretical studies have analyzed the incentives of producers to invest in the safety of AVs (see, e.g., Di, Chen, and Talley, 2020; Friedman and Talley, 2019), which is combined with the consideration of the (optimal) precaution level of drivers (see, e.g., Shavell, 2020; Guerra, Parisi, and Pi, 2022). This literature stresses the importance of the liability regime in place for generating appropriate incentives. However, certain, yet unresolved, issues with respect to product and criminal liability in the context of AVs (see, e.g., Geistfeld, 2017; Gless, Silverman, and Weigend, 2016) still contribute to the uncertainty producers and users of AVs face.

Among the papers examining (optimal) behavior of AV producers and drivers, only a few explicitly consider the choice of vehicle buyers between purchasing an AV or a conventional car (CV). De Chiara et al. (2021) consider a multi-stage game-theoretic model in which a monopolistic AV producer first decides on how much to invest in the AV safety level and which price to set for the AV, and the consumers then decide between purchasing an AV or a CV (which is sold on a perfectly competitive market) and, if they purchase a CV, determine their (costly) level of precaution when driving. Their setting allows to study factors influencing the market penetration of AVs, with their focus set on the comparison of the implications of different liability rules. A related agenda is pursued in Dawid and Muehlheusser (2022), who developed a dynamic model with a monopolistic AV producer, which over time build up the AV safety level, and heterogeneous consumers, who at each point of time choose between AVs and CVs. Their dynamic framework with endogenous demand evolution allows them to distinguish between short and long run effects of different liability schemes on AV sales, accident rates, and welfare.

Our paper complements this stream of literature in several ways. First, we focus on firms' market introduction strategies rather than on their R&D investment, as it has been done in this literature so far. Second, we put the uncertainty associated with the technological development of AVs as well as with their perception among consumers center stage and study the implications of communication processes as well as the consumers' attitude toward uncertainty for AV diffusion in general and for the relative performance of different product launch strategies in particular.

2.2 Product Launch Strategies

Although product launch strategies have so far not been studied in the context of AVs, there is considerable literature analyzing this problem for durable goods, some of it with quality increasing over time. The works by Krankel, Duenyas, and Kapuscinski (2006) and Lobel et al. (2016) are related to our contribution in the sense that, like us, they study product launch strategies under the assumptions that the evolution of the technology level is exogenous and stochastic, and that a firm launching a new model always takes the old one from the market. However, contrary to our setting, the predecessors do not consider market competition. Furthermore, they assume that all consumers are perfectly informed about all properties of the model that is currently available on the market, whereas we explicitly take into account that in the context of AVs there is substantial uncertainty of consumers about performance and safety of the vehicles already on the market.

Krankel, Duenyas, and Kapuscinski (2006) study the firm's optimal launch strategy under the assumption that sales in every period depend (in a way similar to the well known Bass diffusion model) on cumulative sales and a market potential, which increases with the current technology level but not on consumer expectations regarding the performance of future models. They show that with such 'myopic' consumers it is optimal for the firm to launch the next product once the current technology is above a threshold, which depends monotonously on the technology of the product currently on the market and non-monotonously (inverted U-shaped) on cumulative sales.

Lobel et al. (2016) incorporate forward-looking consumers into a framework which is otherwise similar to Krankel, Duenyas, and Kapuscinski (2006). In their setting, consumers are not influenced by cumulative sales but rely on intertemporal optimization, taking into account the (expected) properties of models introduced in the future, to determine whether it is optimal for them to purchase the product currently on the market. In such a setting, it is important for the consumer expectations and, hence, their behavior whether the firm commits to a schedule of technology levels, at which it will introduce new models, or avoids such commitment, in which case consumers rationally expect that the firm will introduce new models at technology levels where its own value is maximized. Lobel et al. show that without commitment, the firm's optimal strategy implies to keep introducing new products once the ratio between the firm's current technology and that of the product it offers on the market exceeds a certain constant threshold. With commitment under certain conditions, a two-cycle strategy is optimal, in which a large and a small technology jump between new models alternate. Numerical analyses suggest that by committing in advance to the optimal launch strategy the firm can improve its profit between 4% and 12%.

In our paper, we restrict attention to strategies in which the firm commits in advance, but compare the effects of commitment to performance and safety versus commitment to the time of the new product launch. We assume that consumers are forward-looking and base their decisions on expectations about the properties or the time of the next product launch, respectively. However, in light of the substantial uncertainty under which consumers act in our setting, we assume that expectation formation and consumer decision making rely on heuristics rather than on rational expectations and dynamic optimization as in the model by Lobel et al. (2016).

2.3 Agent-based Modeling of Innovation Diffusion

Predicting the resulting innovation diffusion as an outcome when applying a given set of management measures is difficult. The reason why is that a consumer market constitutes a complex system, in which diverse stakeholders (i.e., consumers, distributors, competitors, etc.) act according to their individual aims and needs, and they interact and, thus, influence others in various ways (e.g., through producers announcing new products or consumers among themselves when engaging in word-of-mouth communication).

In this setting, ABM has become an established method for innovation diffusion research. It represents stakeholders by agents with individual preferences, knowledge (beliefs), and behaviors, and beyond that, it only requires the encoding of micro-rules governing the behavior of involved stakeholders (i.e., agents) in order to be able to observe emergent macro-level behavior of the market. For an early review on ABM in innovation diffusion research, see Garcia (2005); an often-cited survey is provided by Kiesling et al. (2012). Examples of applications from other disciplines are given by Macal (2016); for the field of marketing, see Rand, Rust, and Kim (2018).

Recently, Rand and Stummer (2021) discuss strengths and criticisms of ABM of new product market diffusion. Among the strengths, first, ABM can account for the heterogeneity of diverse stakeholders across a population (e.g., from innovators to laggards, according to their innovativeness as described by Rogers, 2003). Second, stakeholders can be treated as individuals by keeping track of the experiences of each agent during the course of a simulation run. Therefore, an agent's individual attitude toward a certain product attribute results from the history of this agent's decisions, the agent's internal notion of the external world, the agent's observation of the reactions of other agents in response to their actions, and the agent's retained memory of past events (Macal and North, 2010). Third, modelers can choose between various decision-making rules to be used by the agents such as preference matching, stage-based approaches, utility maximization, meeting required thresholds, etc. (for a detailed description, see Negahban and Yilmaz, 2014). Fourth, interaction between stakeholders, usually in the form of word-of-mouth communication as well as advertisement, and corresponding informational influence can be taken into account (for a comparison of ABM and different equation models, see Rahmandad and Sterman, 2008). News from media can play a similar role as word-of-mouth communication albeit it has to be modeled as a unidirectional information exchange from a media agent to a set of consumer agents. Fifth, ABM offers a testbed for strategies before they are employed in actual markets and, thus, provides an opportunity to analyze conditions under which the diffusion of innovations succeeds or fails (e.g., Backs et al., 2021; Haurand and Stummer, 2023; Stummer, Lüpke, and Günther, 2021).

Among the criticisms, Rand and Stummer (2021) discuss the sometimes challenging parameterization, the need for a proper verification and validation, issues regarding arbitrariness and lack of causality, as well as computational cost incurring for simulation experiments. All the above are valid concerns and demand adequate attention. However, Rand and Stummer conclude that ABM has the ability to capture emergent phenomena and allows for high flexibility in representing diverse market settings.

2.4 Agents' Interactions in Social Networks

More often than not, market diffusion of innovations is driven through social influence that is exerted as informational influence, which refers to accepting information obtained from others as evidence of reality (e.g., through word-of-mouth communication or advertising). It occurs through interaction between consumer agents who are interconnected in a social network. For an in-depth discussion on modeling social influence in ABM for innovation diffusion, see the survey by Kiesling et al. (2012).

The social network describes social ties between agents (e.g., representing the entries in their smartphones' contact lists). Real social networks exhibit a relatively small diameter (i.e., longest shortest path length between two agents), many clusters (i.e., groups of agents who are strongly interconnected with each other), and numerous hubs (i.e., certain agents have a large number of contacts). Usually, a social network is created either as a small-world network following the generation algorithm by Watts and Strogatz (1998) or as a scale-free network following the generation algorithm by Barabási, Albert, and Jeong (1999). The decision for one or the other approach depends on the specifics of a market under investigation (see also Negahban and Yilmaz, 2014).

Word-of-mouth communication can take place between two (or even more) agents who are directly interconnected in the social network. Modelers have to decide (i) who triggers the information exchange (e.g., each agent starts a new conversation after a certain period of time) or through which event it is triggered (e.g., when an existing product is not working any longer and an agent is looking for a replacement), (ii) whether the information flow is unidirectional or bidirectional, (iii) which type of information is transferred (e.g., just the current attitude as a mean of all information received so far or a distribution of all this information, thus also representing a measure for the certainty of the sender regarding the accuracy of the information), (iv) whether the confidence that the sender provides correct information (e.g., the sender being only a novice in the respective field or she being already an expert) on the part of the receiver plays a role, and (v) the way the additional information is processed in order to reach an updated value for the receiver's attitude. An illustrative example for word-of-mouth communication in ABM of innovation diffusion can be found in the work by Stummer et al. (2015).

3 Model

When setting up an ABM as a means for analyzing (i) the effectiveness of two generic announcement strategies for the market introduction of novel generations of AVs, (ii) the impact of technology curves and consumer heterogeneity, and (iii) the role of uncertainty on the sides of the producers and the consumers, we drew from three strands of prior research. First, we build on substantial experience in modeling market diffusion of innovation and on implementing such models in simulation tools. Second, in capturing factors influencing the purchase intention of AVs we rely on empirical evidence reported by Topolšek et al. (2020) with subjects from Slovenia and Croatia in 2019–2020. Results indicate that car safety and performance expectancy have the highest positive effect on purchase intention, which is why we focused on these factors in our model.[4] Third, we capture in our model that uncertainty of consumers about AV quality is influenced by signals they receive on the one hand through social networks and the media.

In the following, we present our economic model. In doing so, we describe the key assumptions and components of the model, in particular the different agent types and how they interact.

[4]Interestingly, a higher level of education seems to reduce purchase intention. The same holds for anxiety while higher age has a positive effect. However, the effects were low compared to car safety and performance expectancy and, thus, we disregarded the above factors for reasons of simplicity (but, in principle, could extend our model in a future version). The assumed effects of all other factors investigated by Topolšek et al. (2020) were not significant.

3.1 Car Producers and Technology

On the supply side, the market for vehicles consists of N AV producers. Additionally, conventional vehicles (CV) requiring a human driver are offered by a group of separate producers, which we do not model explicitly. Whereas safety and performance of AVs changes over time, we assume that for CVs these properties are constant. CVs therefore serve as an outside option for consumers who are not satisfied with any of the AV models offered on the market.

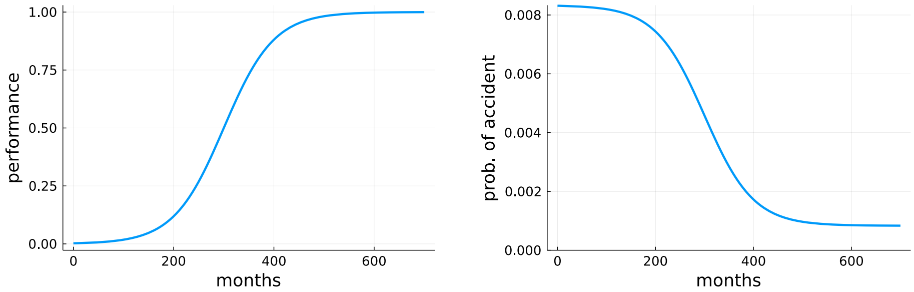
For the purpose of this paper, we abstain from explicitly modeling R&D activities by the producers and assume that the level of AV technology available to a producer is determined by randomly arriving innovation instances at which the producer jumps (close) to the evolving technological frontier. AV technology consists of two independent components, namely, the AV's performance and the AV's probability of accident. The probability of an accident, denoted by $p(t)$, is used as a proxy for the AV's safety; performance, denoted by $q(t)$ is meant to cover all other aspects relevant to consumers when purchasing an AV, such as the capability of driving autonomously under different conditions (e.g., highway vs. city center), the ride comfort, the efficiency (e.g., lane selection, anticipatory driving) and so on.[5] We refer to the combination of performance and safety as the (overall) quality of the technology. Following existing literature on innovation diffusion (e.g., Foster, 1986), we assume that the two technology curves, describing the evolution of the two frontiers over time, are s-shaped functions of time t with the following functional form:

$$(1) \quad a\left(t\right) = a^{-\infty} + \left(a^{\infty} - a^{-\infty}\right)\left(\frac{1}{1 + \exp\left(-a^{\text{shape}}\left(t - a^{\text{shift}}\right)\right)}\right),\ a \in \{p, q\}$$

where $a^{-\infty}$ and a^{∞} denote the asymptotic values of the curve for $t \to -\infty$ respectively $t \to \infty$, a^{shape} governs the shape of the function and a^{shift} shifts the function to the left or right. Figure 1 shows the technology curves used in the baseline for performance and the monthly probability of accident. We assume that firms can perfectly observe the performance available at the technological frontier, but only receive a noisy signal of the safety component. This reflects that the safety of the newly developed AV technology is inherently difficult to assess, even for the producer itself, since training for AVs to a large extent relies on opaque machine learning methods (see Di and Shi, 2021).

Given the s-shaped curves, technological progress is typically slow in the beginning, speeds up rapidly after a breakthrough has been made and flattens out again, when the AV technology has been almost fully developed. We assume that the innovation times of producers are stochastic and arrive at rates λ^{q} for the performance component and λ^{p} for the safety component. As soon as a firm discovers an innovation, its performance or safety level jumps to the value on the respective technological frontier modified by a stochastic noise term $\sigma^{m}athrma$.

[5] The variables $p(t)$ and $q(t)$ refer to the technological frontier values of accident probability and performance, whereas the corresponding values for a producer j are denoted by $p_j(t)$ and $q_j(t)$.



(a) *(b)*

Figure 1
Technology curves for (a) performance and (b) probability of accident.

If such a jump occurs at time t, Firm j's available technology with respect to performance or safety is then given by

$$a_{j,t} = a(t) + N(0, \sigma^a). \tag{2}$$

As a result, producers in general differ with respect to the level of AV technology available to them, resulting in a firm which is technology leader and firms that are lagging behind. As discussed above, the probability of accident cannot be fully observed and the producer instead observes a noisy signal about the AV's true probability of accident given by $\tilde{p}_{j,t} = p_{j,t} + N(0, \sigma^{\text{obs}})$.

Firms cannot bring every single step of technological progress into the market immediately but have to decide on discrete points in time at which a new vehicle model is introduced to the market. The newly released model then corresponds to the level of technology available to a firm at the time of release. Even though we do not directly model the costs of introducing a new model, we assume that firms cannot release new models arbitrarily often in time but have to employ a certain release strategy. We distinguish between two prototypical types of strategies, which we refer to as (i) the *time strategy* and (ii) the *quality strategy*. Employing a time strategy means that the producer releases new models in regular intervals, independently from the progress in technology that has been made compared to the previous model. In contrast, employing a quality strategy means that the producer targets a certain constant (minimum) absolute quality difference between two models and releases a new model as soon as this difference has been reached. Hence, the quality strategy introduces new models irregularly in time. Whenever a producer introduces a new model, it discloses information about performance and the probability of accident of the new model to all potential customers. Although producers do not strategically spread misleading information, the signal on the probability of accident may be inaccurate since safety cannot be fully observed by the producer itself. Every time a new model is released, the producer also provides information about its plans for the future: in case of the time strategy, it announces a fixed release date of the future model, while in case of the quality strategy, she commits to a certain level of performance and safety for the next model. This implies that there is no information about future performance and safety in the first case and no information about the release date of future models in the second case.

3.2 Consumers

Every consumers in our model owns and drives a car, which she has to replace from time to time. At the beginning of the simulation, every consumer owns a CV. Whenever a vehicle has to be replaced, the consumer chooses between CV and AV, and—if she intends to purchase an AV—between the different producers. We assume that each consumer $i \in [1, M]$ has a minimum and maximum preferred vehicle lifetime, $v_i^{\min}$ and $v_i^{\max}$, and will only consider purchasing a new vehicle when her current vehicle's age exceeds $v_i^{\min}$. If so, the consumer has three elementary options: (i) she can purchase a CV, (ii) she can purchase an AV, (iii) she can wait for the release of a new (and better) AV model. The third option, however, is only available if the age of the consumer's current vehicle is below $v_i^{\max}$. In the following, we will describe how consumers choose between the first two options and discuss under which conditions she decides to wait for the release of a new AV model.

Each consumer i has an individual minimal performance and maximum probability of accident threshold $(q_i^{\min}, p_i^{\max})$. Generally speaking, a consumer will always decide in favor of an AV if her performance and accident probability thresholds are met and take the CV as an outside option otherwise. However, consumers cannot directly observe the performance and accident probability of vehicle models on the market and have to rely on their individual perception of or belief about these values in order to make a decision. Let K_t denote the set of AVs available at time t. In order to capture a certain consumer's potential uncertainty, we assume that the consumer's perception of the performance of an AV model $k \in K_t$ is represented by a random variable $Q_{i,k,t}$ distributed according to a distribution with a cumulative distribution function (CDF) given by $F^{\mathrm{q}}_{i,k,t}(q)$. Similarly, her perception of accident probability $P_{i,k,t}$ is represented by a distribution with CDF $F^{\mathrm{p}}_{i,k,t}(p)$. These distributions are initialized using the producer's information on performance and accident probability at the time of release and may change over time (see Section 3.3). Given this setup, a consumer cannot tell with certainty that her thresholds are met by a given AV model. Therefore, each consumers also has an individual minimum probability threshold $\theta_i \in [0, 1]$ which represents her attitude toward uncertainty. A consumer will only buy an AV, if she beliefs that the AV's performance is above her performance threshold with probability θ_i and that the AV's performance of accident is below her probability of accident threshold, again with probability θ_i. Consumers with a low value of θ_i will accept substantial uncertainty, whereas consumers with a high value of θ_i require a high degree of certainty, before deciding to purchase an AV. If there is at least one acceptable AV on the market, the consumer selects the one which offers the higher joint probability that her performance and safety requirements are met. If there is currently no acceptable AV on the market, but the consumer expects that a new AV model satisfying her requirements will be released in time, she postpones her decision. More precisely, the decision between the different options is determined as follows: Let z_i denote the time of consumer i's last purchase of a new vehicle. For each point in time $t \in \left[z_i + v_i^{\min}, z_i + v_i^{\max}\right]$, with probability $\zeta \in (0, 1]$ the consumer considers the following options:

Option 1: Purchase a currently available AV. For each vehicle model $k \in K_t$ on the market, calculate the probability $P^{\mathrm{q}}_{k,i,t}$ that the vehicle's performance is above the consumer's performance threshold according to her beliefs as $P^{\mathrm{q}}_{i,k,t} = 1 - F^{\mathrm{q}}_{i,k,t}(q_i^{\min})$. Similarly, calculate the probability $P^{\mathrm{p}}_{k,i,t}$ that the vehicle's probability of accident is below the consumer's accident probability threshold as $P^{\mathrm{p}}_{i,k,t} = F^{\mathrm{p}}_{i,k,t}(p_i^{\max})$. Select the subset $K^*_{i,t} \subseteq K_t = \{k \in K_t | P^{\mathrm{q}}_{i,k,t} \geq \theta_i \wedge P^{\mathrm{p}}_{i,k,t} \geq \theta_i\}$ consisting of all the vehicles satisfying the consumer's requirements. Then, for every element of this subset, calculate the joint probability that a vehicle model satisfies both requirements and select the vehicle with the highest probability. Formally, if $K^*_{i,t}$ is not empty, purchase the vehicle $k^*_{i,t}$ selected according to

$$k^*_{i,t} = \arg \max_{k \in K^*_{i,t}} \left[P^{\mathrm{q}}_{i,k,t} \cdot P^{\mathrm{p}}_{i,k,t}\right]. \tag{3}$$

If $K^*_{i,t}$ is empty, consider Option 2.

Option 2: Wait for a better AV. Let $\tilde{K}_t$ denote the set of AVs that have been announced by producers. First, for each $k \in \tilde{K}_t$, determine the expected release date $\hat{t}_k$. If the model has been announced by a producer employing the time strategy, this is simply the announced date. If the producer employs a quality strategy, the expected release date is the time of the latest release plus the time difference between the two last release dates of this producer. Next, for each $k \in \tilde{K}_t$, determine the expected beliefs about performance and accident probability $\hat{F}^{\mathrm{q}}_{i,k,\hat{t}_k}$, $\hat{F}^{\mathrm{p}}_{i,k,\hat{t}_k}$ at the expected release date. In case of the quality strategy, these can be determined taking the information on performance and accident probability from the announcement. In case of the time strategy, the means for performance and accident probability are again determined by comparing the producers latest release with the release before and assuming a linear improvement in technology. Calculate the probabilities that the vehicle will satisfy the consumer's requirements at the time of release $\hat{P}^{\mathrm{q}}_{i,k,\hat{t}_k}$, $\hat{P}^{\mathrm{p}}_{i,k,\hat{t}_k}$ as described under Option 1. Next, consider the subset

$$\tilde{K}^*_{i,t} = \{k \in \tilde{K}_t | \hat{t}_k \leq z_i + v_i^{\max} \wedge \hat{P}^{\mathrm{q}}_{i,k,\hat{t}_k} \geq \theta_i \wedge \hat{P}^{\mathrm{p}}_{i,k,\hat{t}_k} \geq \theta_i\}. \tag{4}$$

If $\tilde{K}^*_{i,t}$ is non-empty, wait for the release of a new AV. Otherwise, proceed with Option 3.

Option 3: Purchase the CV. If none of the currently available AVs is satisfactory and the consumer does not expect that a new satisfactory AV will be introduced before her current vehicle exceeds her maximum preferred vehicle lifetime, she decides to buy the CV as an outside option.

3.3 Formation and Updating of Beliefs

As the consumers' beliefs regarding vehicles performance and accident probability of the AVs on the market play an important role in the consumer's decision making process, they are crucial also with regard to the diffusion of AV technologies. In the following, we explain how the beliefs are initialized and updated over time.

Initialization of beliefs. We assume that all agents have normally distributed beliefs over performance and accident probabilities of AV models. Hence, beliefs are fully characterized by the mean and the standard deviation of the respective distribution.[6] Whenever a new model k is introduced, the producer (truthfully) publishes information on the vehicles performance q_k and accident probability p_k. If this producer has not released an AV before, all agents initialize their beliefs by setting $Q_{i,k,t} \sim N(q_k, \sigma^{\mathrm{q}}_{\mathrm{ini}})$ and $P_{i,k,t} \sim N(p_k, \sigma^{\mathrm{p}}_{\mathrm{ini}})$, where $\sigma^{\mathrm{q}}_{\mathrm{ini}}$ and $\sigma^{\mathrm{p}}_{\mathrm{ini}}$ represent the maximum initial uncertainty consumers can have in the model. This uncertainty may be reduced in subsequent iterations of the model. If a producer which already has an AV on the market releases a new AV model, we assume that consumers do not initialize their beliefs with maximum uncertainty but instead take their beliefs about the previous model of the producer into account. Assume that a consumer has the following belief about the performance of an existing AV model $\tilde{k}$: $Q_{i,\tilde{k},t} \sim N(\mu^{\mathrm{q}}_{i,\tilde{k},t}, \sigma^{\mathrm{q}}_{i,\tilde{k},t})$. If the producer introduces a new AV model k with performance q_k, the consumer initializes her belief about the new model's performance as

$$Q_{i,k,t} \sim N\left(q_k, \gamma\sigma^{\mathrm{q}}_{i,k,t} + (1-\gamma)\,\sigma^{\mathrm{q}}_{\mathrm{ini}}\right), \tag{5}$$

where $\gamma \in [0,1]$ is calculated as $\gamma = g_{\mathrm{q}}(|q_k - \mu^{\mathrm{q}}_{i,\tilde{k},t}|)$, with ${g_{\mathrm{q}}}' < 0$, taking the difference between the announced performance and the mean performance according to the belief about the existing model's performance into account. The rationale behind this assumption is that consumers will be less uncertain about a new AV model if it is similar to an existing one and will face higher uncertainty if the producer claims that the new AV, for example, has a considerably higher performance as the previous one. Beliefs about the probability of an accident are initialized in an analogous way by using $\sigma^{\mathrm{p}}_{\mathrm{ini}}$ and the function g_{p}.

[6] Strictly speaking, the assumption of normally distributed beliefs implies that consumers also allocate positive probability to negative values of these variables. However, under our parameterization, these probabilities are always negligible and therefore we make this assumption for analytical convenience.

Updating the performance belief. There a two possibilities for an update of the performance belief about an AV: (i) through first-hand experience (available only for users of an AV) or (ii) through communication with peers in the social network. In both cases, consumers receive a signal about the performance of an AV and we employ Bayesian learning (Baley and Veldkamp, 2023) to update the consumer's belief.[7]

At every point in time t, with probability ϕ^{use}, an AV owner using an AV model of type k receives a signal about her own AV's performance. The signal is given by $s \sim N(q_k, \sigma^{\text{use}})$, where q_k denotes the true AV's performance and σ^{use} is a parameter representing noise in the owner's AV experience. The AV owner uses the signal to perform a Bayesian update of her belief about the AV's performance, resulting in a new value for the mean as well as the standard deviation. If an AV owner received a signal as described above, she will potentially distribute the new information via her social network. To model social ties between agents, we employ a spatial version of the algorithm introduced by Barabási, Albert, and Jeong (1999), which creates a scale-free network with high clustering and small diameter (Stummer et al., 2015). Let χ_i denote the set of consumer i's contacts as given by the social network. For every friend $l \in \chi_i$, consumer i with probability ϕ_i^{talk} sends a signal about the AV's performance given by

$$s \sim N\left(\mu^{\text{q}}_{i,k,t}, \frac{1}{2}\left(\sigma_i^{\text{comm}} + \sigma_l^{\text{comm}}\right)\right), \tag{6}$$

where $\mu^{\text{q}}_{i,k,t}$ represents consumer i's own perception of the AV's mean performance and $\sigma_m^{\text{comm}}, m \in \{i, l\}$ denotes the communication competence of the two consumers. Similar as above, consumer l uses the signal to perform a Bayesian update of her own belief about AV k's performance.

Updating belief about probability of accident. In order to update consumers' beliefs regarding AV accident rates, in each iteration, we simulate traffic in a simplified manner: We assume that each month, each consumer experiences x occasions where an accident could occur. At each of this occasions, we report an accident with probability p_k if the consumers drives AV model k and with probability p_{CV} if she drives a CV. This results in a certain number of accidents for each AV model currently used by consumers as well as the total number of accidents caused by CV drivers. We collect data for 12 months and then estimate the accident probability $\hat{\mu}^{\text{p}}_{k,t}$ as well as the standard deviation of the estimator $\hat{\sigma}^{\text{p}}_{k,t}$ for each AV model used in that time interval. We assume that these estimates are published via the media and every consumer receives this information with probability ϕ^{media}. Consumers who receive this information treat it as a signal $s = \hat{\mu}^{\text{p}}_{k,t} \sim N\left(\hat{\mu}^{\text{p}}_{k,t}, \hat{\sigma}^{\text{p}}_{k,t}\right)$ and employ Bayesian updating to update their belief about AV model k's probability of an accident.

[7] For a brief description of Bayesian learning see Appendix B.

4 Calibration

To calibrate our model for the German market, we employed a mixed methods approach and combined a qualitative-empirical study with a quantitative-empirical one. For the qualitative-empirical study, two interviews with car salesmen and three interviews with potential consumers of AVs were conducted. The former two interviews served as a solid basis for understanding both the announcement strategies of car producers as well as car purchasing behavior. The latter three interviews provided more detailed insight into the purchasing processes including possible key buying factors. These factors were then investigated in a subsequent quantitative-empirical study, whose results we used to populate our simulation with agents that are heterogeneous in certain key properties. All other parameters have been chosen in a way to reflect empirical evidence whenever possible. In the following, we describe how we conducted the quantitative survey and incorporated the results in our simulation. The full list of parameter values can be found in Appendix C.

4.1 Sample

Participants were recruited via the panel provider Bilendi (www.bilendi.de), which guaranteed that all participants were car owners, from Germany, and at least 18 years old, and that the sample was representative of the population in Germany with respect to age and gender. Still, small discrepancies from official statistics can be found due to the ex-post exclusion of certain responses, which happened when participants failed to correctly answer attention checks (e.g., “Please tick the ‘strongly disagree’ box”), when we found specific patterns in response behavior (e.g., ticking the same answer on the scale for most questions), or when we identified uncommon response times (e.g., extraordinarily long or short response times or breaks when answering the questionnaire). Several of the above issues were found in all the responses that were excluded. The final sample included responses from 265 participants (51.3% female; $M^{\text{age}} = 45.8$; $SD = 14.0$).

4.2 Procedure

Addressing the quality strategy, we measured the *importance of performance* inspired by Sujan and Bettman (1989) by means of four items: *“The performance of an autonomous car is important”*; *“The performance of an autonomous car is relevant to my purchase intention”*; *“I would only buy an autonomous car, if my requirements referring to performance are fulfilled”*; and *“Referring to performance, it is important that all functions of the autonomous car are fully developed”* ($\alpha = 0.910$).[8]

As another variable, we also measured the *importance of safety* by asking participants about acceptable car accident rates for AVs using the probability

[8] Cronbach’s alpha (α) is a reliability coefficient measuring internal consistency of a scale (Cronbach, 1951).

of 5% to be involved in a car accident per year for conventional cars (Kords, 2022; Destatis, 2022) as an anchor point: *"I would take an autonomous car into consideration if the car accident rate per year is below 5%"*; *"I would take an autonomous car into consideration if the car accident rate per year is about 5%"*; and *"I would take an autonomous car into consideration if the car accident rate per year is above 5%"*.

Next, we used four items adapted from Wang, Yu, and Wei (2012) to measure *peer communication*: *"I talk to other persons about autonomous cars"*; *"I talk to other persons about buying an autonomous car"*; *"I ask other persons for advice about autonomous cars"*; *"I obtain information about autonomous cars from other persons"*; and *"Other persons encourage me to buy an autonomous car"* ($\alpha = 0.946$).

Three items adapted from Rubin and Martin (1994) were used to measure *communication competence*: *"When I talk to family members/friends about autonomous cars, the conversations are easy to understand"*; *"In conversations with family members/friends about autonomous cars, I perceive not only what they say but what they do not say"*; and *"I am able to take charge of conversations about autonomous cars so that my family members/friends can understand the topic we talk about"* ($\alpha = 0.877$).

Based on the results of our qualitative-empirical study, we also added two items concerning consumer's *attitude toward uncertainty*: *"I would buy an autonomous car, even if there is insufficient information about that autonomous car"*; and *"I would buy an autonomous car, even if there is inconsistent information about that autonomous car"* ($\rho = 0.932$).[9]

Lastly, we included questions referring to the *minimum and maximum lifetime* of CVs: *"What is the minimum duration during which you use your conventional car?"* and *"What is the maximum duration during which you use your conventional car?"*.

4.3 Mapping results to the simulation

In order to use the survey data to initialize and populate the simulation model, participant's responses have to be mapped from the scale used in the survey (possible discrete answers ranging from 1 to 7) to values that are appropriate in the context of the model. First, for each participant, we take the average response value from all items belonging to one construct. Second, we linearly transform this average to a range of decimal numbers which is reasonable for the respective agent property. Table 1 shows the mapping between survey constructs and the respective agent properties as well as the minimum and maximum values used. Apart from the constructs shown in Table 1, we also used the minimum and maximum vehicle lifetime to inform the agent properties $v_i^{\min}$ and $v_i^{\max}$. However, in this case the values from the survey can be used directly

[9] The Spearman–Brown formula (ρ), which is also a reliability coefficient measuring internal consistency of a scale, is used in case of scales consisting of two items (Brown, 1910; Spearman, 1910).

without a mapping. In order to be able to create agent populations of arbitrary size, we performed a multivariate kernel density estimation (KDE) using the transformed survey data and initialized the model by sampling agent properties from the KDE distribution. For a visual representation of the KDE result by marginal distributions, see Appendix A.

Table 1
Mapping of survey constructs to agent properties.

Construct	Property	Min	Max
Importance of performance	$q_i^{\min}$	0.05	0.95
Importance of safety	$p_i^{\max}$	0.02	0.08
Peer communication	ϕ_i^{talk}	0.0	0.04
Communication competence	σ_i^{comm}	0.05	0.25
Attitude toward uncertainty	θ_i	0.1	0.9

5 *Firm Strategy and Competition*

In order to compare the two prototypical strategies, we consider a duopoly scenario as a baseline, where one of the producers employs a time strategy and the other employs a quality strategy. The time strategy producer releases new AV models in regular intervals of τ months, whereas the quality strategy producer releases a new AV model as soon as the performance and safety levels have been improved by some constant value since the last product release. In order to make the two strategies comparable, for each scenario, this number has been calibrated such that the average number of AV models released in the considered time frame of 700 months is the same compared to the time strategy. Our analysis is based on batches of 100 simulation runs, carried out in each considered strategy scenario and parameter constellation.

5.1 Baseline Scenario

Figure 2 shows our results for the baseline scenario. Figure 2a depicts the evolution of the total number of AV owners over time by means of average values and quantil intervals. Although a few consumers prefer and purchase AVs from the start of the simulation, overall sales numbers and the share of AV owners are very low until around iteration 300, and subsequently begin to significantly rise up to around 55% at the end of the simulation horizon. The low number of sales in the beginning of our simulation runs can be attributed to the low level of technological development at that time.

Figure 2b depicts the average annual accident rate of all vehicles in use (CV+AV). For the first half of the simulation, the accident rate fluctuates around 5%, which resembles the accident rate for traffic by CVs in Germany.

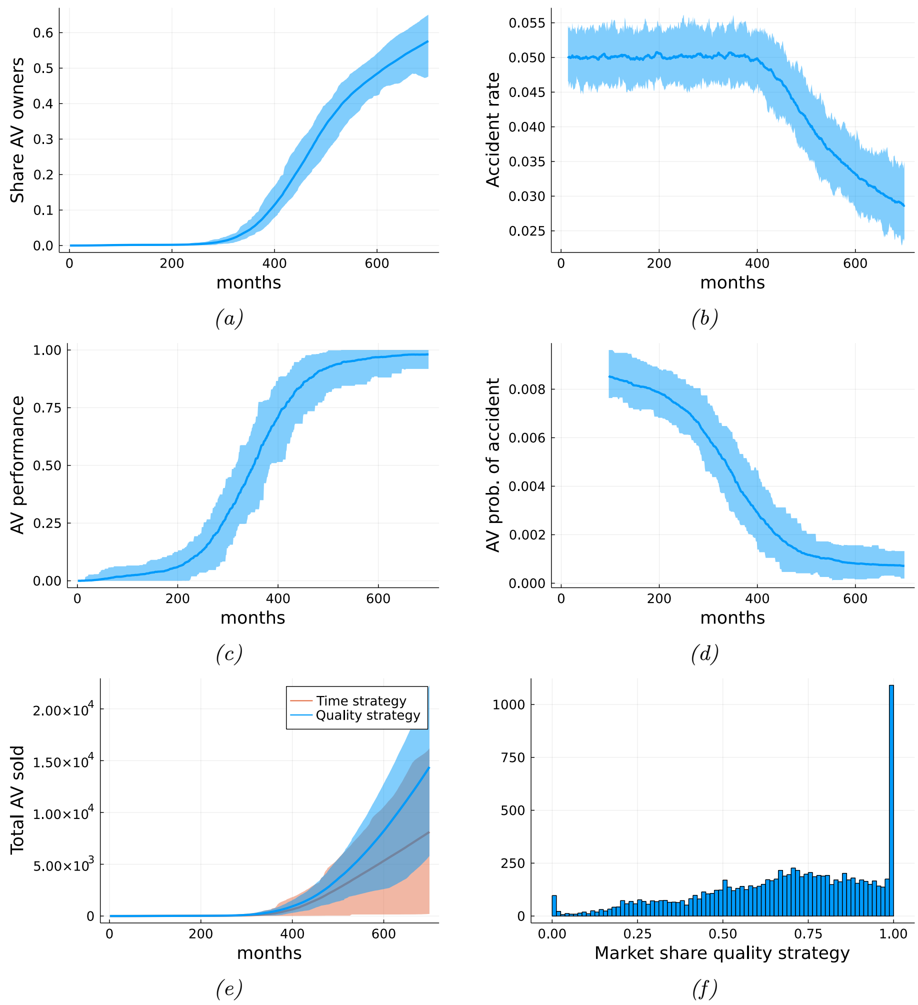


Figure 2

Baseline simulation runs: (a) The share of AV owners, (b) the overall accident rate (CV+AV), (c) the average performance and (d) average monthly accident probability of AVs on the market, (e) total AV sales by the time strategy and quality strategy producer, (f) market share of the quality strategy producer during the final 100 iterations of the simulation. The solid line depicts the mean of 100 runs, the shaded area represents the 95% confidence band.

The accident rate then starts to visibly decline from around iteration 400 as from this point on (i) a growing number of consumers switch from a CV to an AV and AVs therefore gain more and more market share, and (ii) AVs become significantly safer than CVs.

Figures 2c and 2d show the average performance and accident probability of the latest AV offered by the two producers. In the beginning, performance and safety levels are unsatisfactory for the majority of consumers and they still prefer to purchase conventional—that is, human-driven—vehicles (CVs). By comparing Figure 2a to Figures 2c and 2d, it can be noted that the adoption of AV technology is lagging behind the technological development: although the AV technology has been mostly exhausted by the end of our simulation runs and both performance and safety levels are close to their theoretically optimal values, AV adoption is far from complete and the slope of the diffusion curve is already decreasing. The lagged response of consumers to technological advances can be explained by the role of uncertainty for the decision to change to an AV in our model. Accordingly, it is not sufficient that the individual performance and safety requirements are met in expectations but consumers also need to have a certain degree of confidence in their expectation. In fact, uncertainty issues play a major role in practice as was shown by our survey, which indicates that the majority of consumers would only consider purchasing an AV if uncertainty about the AVs performance and safety is low. Unless a consumer already owns an AV, uncertainty regarding properties of the AV can only be reduced by signals received from the social network (regarding performance) and the media (regarding safety). Since the diffusion of information over the social network takes time and does not eliminate uncertainty altogether, the diffusion of AV technology is much slower than the technological development itself.

Figure 2e shows the accumulated total AV sales for each of the two producers. On average, the producer employing a quality strategy sells more AVs and, thus, it can be concluded that the quality strategy performs better in our baseline scenario. However, the variation between runs is high and for some of the runs the time strategy leads to a higher number of total sales.

In order to get a better understanding about the relative performance of the two strategies, Figure 2f provides a histogram of the quality strategies market shares from the last 100 months for all our simulation runs combined. By looking at only the last iterations of each simulation run, we are able to assess what the long-term outcome in particular will look like, e.g., whether one of the two strategies was able to drive the respective competitor out of the market. The x-axis of Figure 2f represents the quality strategies market share from 0% to 100% and on the y-axis, we plot the total number of months observed, in which the quality strategy reached the respective market share. The large bar on the right indicates that around 20% of the runs lead to a monopoly situation, in which only the producer employing the quality strategy survives and the time-strategy producer is fully driven out of the market. In contrast, only very few runs result in the time strategy producer becoming a monopolist. In the remaining runs, the market is split between the two competitors and the quality strategy producer reaches a market share of 68% on average and leads the market in 77% of the observed months, which demonstrates that the quality strategy exhibits a significant advantage in our baseline scenario. By analyzing single-run time series, we can confirm that these results do not stem from often and rapid changes in market shares and that the positions of the two competitors in the market remain fairly stable once they have settled on a certain range of values.

It should be noted that the emergence of a monopoly situation is not driven by differences in parameterization of the two competing firms. In particular, there is no technological difference between the two producers as both producers share the same exogenous technological curve and any difference with respect to quality or safety between the two producers therefore vanishes over time. Hence, the producers offer a homogeneous good in the long-run. Moreover, prices are normalized in the model and there are no capacity constraints or market (re-)entry barriers that could explain emergence and stability of a monopoly. However, we observe path-dependencies related to the existence of uncertainty, which serve as an explanation for the potential emergence of monopolies in our setup. Although both producers objectively offer a homogeneous product at the end of the simulation, consumers' perception of the products' properties may be heterogeneous. Even if consumers have identical expectations about performance and safety of the two AVs on offer, they purchase the one for which their individual uncertainty regarding these properties is lower. Uncertainty is reduced by acquiring new information through the consumers social network (regarding performance) and the media (regarding safety). With respect to both dimensions the extent of uncertainty reduction depends on the number of vehicles a producer has on the road at any given point in time. Since a lower perception of uncertainty is partially carried over to subsequent generations of the AV, the higher number of AVs sold in the past introduces a lasting advantage for the producer. As a result, path dependency plays a role in the diffusion dynamics and a monopoly due to lower perceived uncertainty may emerge.

The discussion above explains why in our model a strategy that gains an advantage with respect to sales is likely to keep that advantage for the future. However, this does not explain why the quality strategy is more likely to gain such an advantage in the first place. In order to understand this observation, we have to turn our view toward the beginning of the simulation around periods 200–400. In this time window, the technological performance and safety levels (Figures 2c, 2d) begin to slowly leave the flat part of the respective s-curves and the technological progress accelerates subsequently. During this time frame, the quality strategy producer on average releases more new AV models compared to the time strategy producer, who is bound to the fixed release schedule. Accordingly, the quality strategy producer exploits technological progress better and, in most runs, offers an AV with better performance and safety levels compared to its competitor. As a result, innovative consumers are more likely to purchase from the quality strategy producer resulting in higher market share. Due to the path dependencies, the quality strategy producer keeps this advantage in most simulation runs.

5.2 Effect of Technology Curves

The above-mentioned reasoning suggests that the competitive advantage of the quality strategy is closely linked to the s-shape of the technology curves. In order to further examine this link, we also tested a scenario in which the technology curves for performance and safety are straight lines with technological progress starting in month 1 and reaching its final and optimal value in month 600. These technology curves model a more rapid technology development as compared to the previously used s-curves from the baseline scenario up until month 300 and from then on fall behind due to the s-curve's higher local growth rate.

Figure 3 illustrates the difference between the flat technology scenario and the s-curve used in the baseline scenario. As expected, adoption of the AV technology starts earlier but at an overall slower rate (Figure 3a). Furthermore, AV adoption at the end of the run is significantly lower in case of the linear technology curves. This result can be attributed to higher uncertainty resulting from the slower adaption of AVs: Since a flat technology curve leads to a delayed adaption particularly by consumers with high performance thresholds, there are also less consumers communicating their experience with AVs, leading to a delay in uncertainty reduction through communication. This effect is not mitigated by the higher initial AV adaption, as the early adopters will only (truthfully) communicate that their AVs have low performance values, which is not helpful regarding the adaption of consumers with high performance thresholds. Regarding market concentration, it is about 4 times less likely than in the baseline case that the quality strategy producers is capable of establishing a monopoly, and the market shares are also in general more evenly distributed (Figure 3b). Still, the quality strategy has a significant advantage, with an average market share of 59% in the last 100 months of the simulation. Other than in the baseline scenario, the quality strategy producer has no possibility of exploiting the s-shaped technological curves in this scenario but it is still able to exploit the technological uncertainty. The reason for the difference between the two strategies is that the producer's current technology level stochastically fluctuates around the shared technology curve and the quality strategy with higher probability triggers the release of a new AV model when the producer's current technology lies above the technology curve, whereas the time strategy producer equally likely release a new AV model, when its technology lies above or below the technology curve. As a result, the quality strategy producer finds better release times and offers better AV technology on average. Hence, employing a quality strategy is more beneficial than using the (inflexible) time strategy. Again, the advantage in the critical time window carries over to subsequent periods but since the advantage is smaller, this is overall less likely to result in a monopoly.

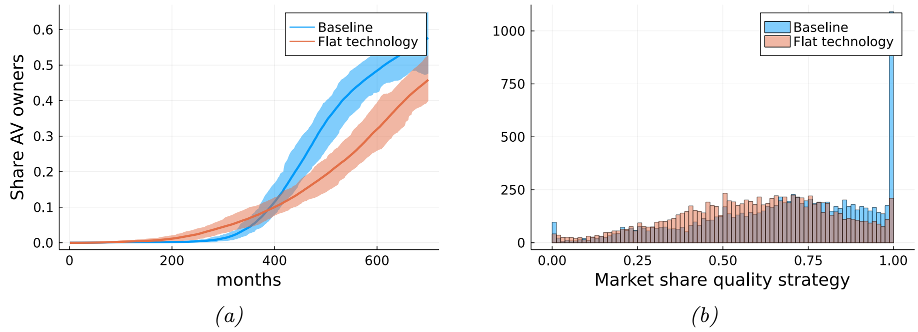
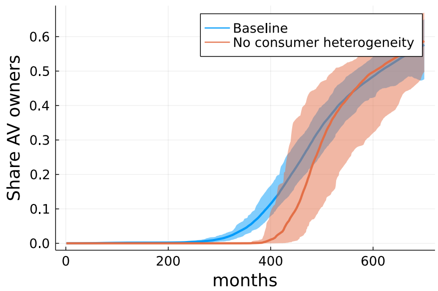


Figure 3
Comparison of the flat technology scenario with the baseline scenario: (a) The share of AV owners, (b) market share of the quality strategy producer during the final 100 iterations of the simulation.

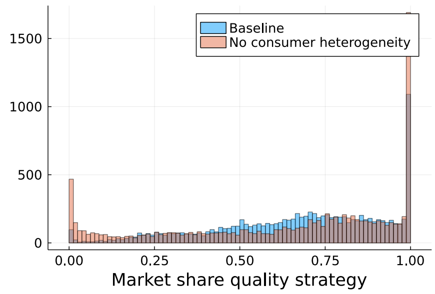
5.3 Effect of Consumer Heterogeneity

Consumer heterogeneity is a distinct feature of our model. In order to examine the impact of consumer heterogeneity on our results, we removed consumer heterogeneity from the model by replacing each of the calibrated behavioral parameters (i.e., $\theta_i, q_i^{\text{min}}, p_i^{\text{max}}, \phi_i^{\text{talk}}, \sigma_i^{\text{comm}}, v_i^{\text{min}}, v_i^{\text{max}}$) by the median of the distribution.

Figure 4 shows the result from the simulation runs in comparison with the baseline scenario. Without heterogeneity among the consumers, AV adoption starts about 100 months later than in the baseline scenario but catches up quickly and is almost at the same level at the end of the simulation. Another major difference between the two scenarios is the increase in variance between runs as can be seen in Figure 4a. The later start of the adoption process can be explained by the lack of consumers who have either a high tolerance for uncertainty (i.e., a low θ value) or low performance and safety requirements and, thus, act as early adopters in the baseline scenario. Since all these potential early adopter have been replaced by the median consumer, adoption takes place at a later point in time but then also at a higher rate, as the homogeneous consumers starts adopting the AV (nearly) all at once. Moreover, also the consumers with high safety and performance requirements or low uncertainty tolerance have also been replaced by the median consumer, which results in lower resistance toward adoption at the end of the simulation. It should be noted that adoption does not happen instantaneously, even though all consumers are identical. The reason why is that (i) at any given point in time only a small subset of consumers consider purchasing a new car and (ii) consumers are identically parameterized but do not share the same beliefs on performance and safety of a particular AV model, since they typically receive diverse information through their social network. Therefore, even though all agent parameters are identical, adopting and non-adopting consumers may still co-exist at the same time in one simulation run. Nevertheless, by examining single-run time series, it can be observed that the adoption curve for a single run typically is very steep after the market introduction of the first successful AV model. However, adoption starts at different points in time and adoption may suddenly stop if, for example, it turns out that the AV has a slightly lower performance or safety than expected. This explains the increase in variance between the simulation runs and the finding that the mean adoption curve does not show any sudden steep increase in AV adoption.



(a)



(b)

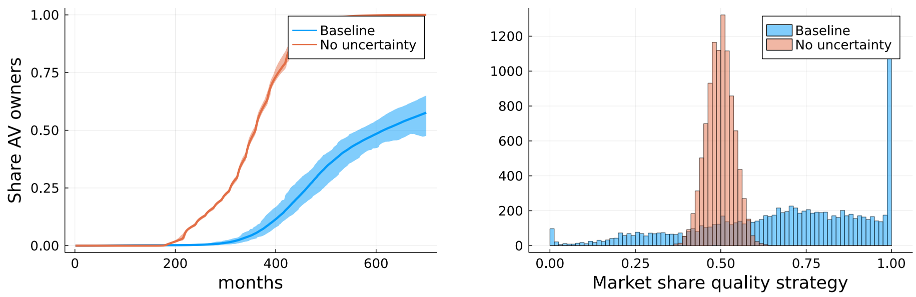
Figure 4
Comparison of the scenario with homogeneous consumers with the baseline scenario: (a) The share of AV owners, (b) market share of the quality strategy producer during the final 100 iterations of the simulation..

Interestingly, a reduction of heterogeneity in our model therefore leads to more uncertainty with respect to the time of the start of AV adoption and the shape of the adoption curve. With respect to market shares (Figure 4b), we observed that a lack of heterogeneity slightly reduces the advantage of the quality strategy. Consequently, the quality strategy producer is less likely to form a monopoly toward the end of the simulation and there are more runs in which the time strategy producer becomes a monopolist. Intuitively, this result is driven by stronger path dependencies arising in the case of homogeneous consumers, which makes it more likely that in runs in which the time strategy producer happens to gain an initial advantage, it is able to extend this advantage to a monopoly position until the end of the run. These findings also underline the importance of capturing heterogeneity in an accurate manner when analyzing the adoption of new technologies.

6 Uncertainty and Consumer Attitudes toward Uncertainty

To demonstrate the importance of capturing uncertainty, we first consider a scenario in which uncertainty is completely removed from the model, that is, more precisely, we assume that there is no technological uncertainty in the sense that producers are able to accurately observe their own technology and consumers have complete trust in all announcements made by producers and information obtained from the media. Furthermore, there is no communication noise when exchanging information through the social network.

Figure 5 shows the result from the corresponding simulation experiments. As can be seen in Figure 5a, AV adoption starts earlier and significantly faster when there is no uncertainty compared to the baseline scenario. The corresponding adoption curve (in the absence of uncertainty) closely resembles the technological performance curve and variance between runs is very limited. This result indicates that AV adoption in the baseline scenario is considerably delayed by uncertainty regarding the properties of AVs and it is not mainly attributed to an actual lack of performance or safety.



(a) *(b)*

Figure 5
Comparison of the scenario without uncertainty with the baseline scenario: (a) The share of AV owners, (b) market share of the quality strategy producer during the final 100 iterations of the simulation.

Uncertainty also has a substantial impact on market shares (Figure 5b). While in the baseline scenario, the AV market exhibits considerable tendencies for market concentration in the long run (up to the frequent formation of a monopoly), in the absence of uncertainty there are no signs of market concentration. Furthermore, the quality strategy has fully lost its advantage, and market shares are evenly distributed among the two producers in the long run. This result is mainly driven by the lack of path dependencies in the absence of uncertainty. If uncertainty does not play a role, a producer cannot profit from increased uncertainty reduction from temporarily having more vehicles on the road, and consequently, this does not create long-lasting advantages.

So far, the reported simulation results were based on the empirically calibrated version of the model, with a large fraction of the consumer population seeking a low level of uncertainty (see Section 4). Accordingly, the number of agents who might adopt the AV technology even though they are uncertain about the AV's properties is low. In the following, we analyze the impact of a change in consumers attitude toward uncertainty. In order to do so, we replace the 'attitude toward uncertainty' parameter of a random subset of consumers (totaling 20% of the population) by a very low value ($\theta = 0.2$). Consequently, the respective consumers not only accept higher levels of uncertainty but also tend to adopt the AV technology in spite of their expectation that the AV does not satisfy their requirements, if uncertainty is high enough to create sufficient upside risk. We refer to such a behavior as 'using uncertainty'.

Figure 6 provides the results from this experiment: AV adoption starts early and is higher at any point in time compared to the baseline case (Figure 6a). However, the difference is mainly limited to the part of the population whose uncertainty threshold has been exogeneously changed by our manipulation. There are no substantial "multiplier effects", which would lead to earlier adoption for agents in the remainder of the population. This can be explained by the fact that AVs during the beginning of the simulation exhibit low performance and safety levels. The earlier adoption by the manipulated agents (who exhibit low θ values) does in fact lead to lower uncertainty also in the remainder of the population. However, since initially the level of actual performance and safety is relatively low, the agents become more certain that they do not want to purchase an AV. As a result from the low safety levels, the accident rate in this scenario exceeds the baseline during the first half of the simulation. However, due to the higher adoption in absolute terms, the accident rate falls below the baseline in the second half of the simulation (Figure 6b). In that sense, there is a trade-off between lower accident rates in the beginning and faster adoption resulting in lower accident rates in the future.

Figure 6c shows that the quality strategy maintains its advantage in the scenario with a high fraction of 'using uncertainty' consumers. However, when looking at the market shares during the final 100 iterations (Figure 6d), it can be seen that market concentration is considerably lower in the 'using uncertainty' scenario and that the quality strategy producer is less likely to form a monopoly. This can be explained by the 20% of the population purchasing AVs in early stages of the simulation at the flatter part of the technology curves, where the quality strategy does not have an advantage over the time strategy.

7 *Conclusions*

The agenda of this paper is to study different key aspects influencing the diffusion of smart products, exemplified by autonomous vehicles. In light of the different types of uncertainties characterizing such products, in particular with respect to their safety—in terms of accident probabilities—and also their future technological development, we compare the performance of two prototypical strategies determining the AV producers' timing of the release of new models.

Using an agent-based simulation model, which we calibrate based on survey data about consumer attitudes toward AVs and the uncertainty associated with them, we show that the quality strategy, under which a new model is introduced once the quality the producer can deliver exceeds the quality of its current model on the market by some fixed absolute difference, outperforms the timing strategy, under which the time between two product releases is constant. In our baseline setting, which incorporates different types of uncertainty associated with AVs and consumer heterogeneity, with substantial probability the producer using the quality strategy is able to take over the entire market, if competing

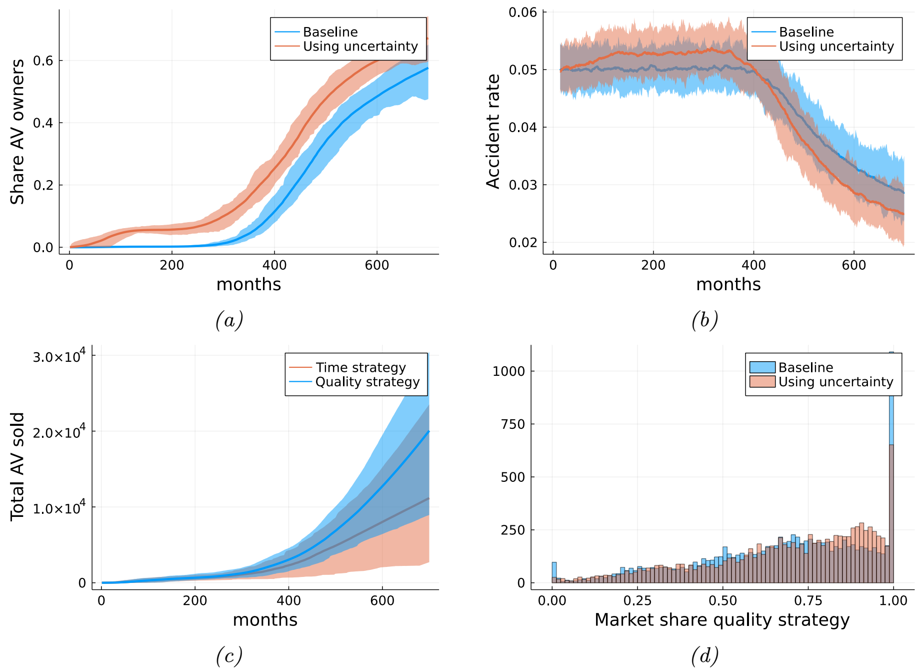


Figure 6
Comparison of the ‘using uncertainty’ scenario with the baseline scenario: (a) The share of AV owners, (b) the overall accident rate (CV+AV), (c) total AV sales by the time strategy and quality strategy producer, (d) market share of the quality strategy producer during the final 100 iterations of the simulation.

with a firm using the timing strategy. If the S-shape of the curve governing the evolution of the technological frontier is less pronounced, the average degree of concentration in the industry is lower—and the long-run share of AVs on the street is smaller—while a reduction in the consumer heterogeneity increases long-run industry concentration.

Furthermore, we show that the tendency toward industry concentration disappears if consumers are certain regarding the quality of (current and future) AVs offered on the market, and that it becomes much smaller if we assume that a larger fraction of the consumers show 'using uncertainty' behavior. An increase of consumers with such behavior also pushes up the share of AV users (in the short and long run) and, thus, induces safer AVs in the long run. Our results show that consumer uncertainty regarding key AV characteristics and the way consumers deal with this uncertainty has not only crucial implications for the speed of AV diffusion but also for the emerging level of industry concentration and the relative performance of the different product launch strategies.

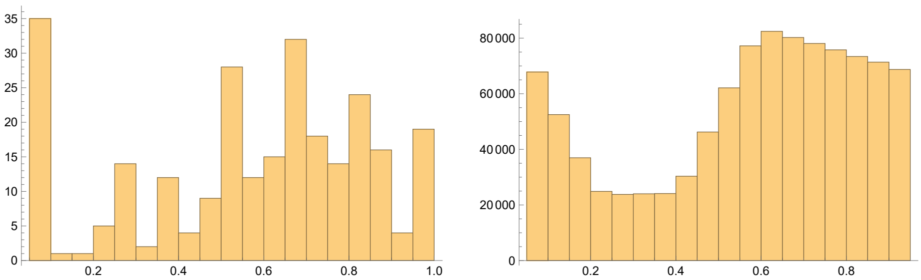
Our analysis has several limitations and can be extended in different directions. First, we assume that consumers' requirements for AV performance and safety, as well as their network of friends, their communication patterns and their attitude toward uncertainty stay constant over time, while it can be expected that several of these properties—and in particular the consumers' perspective on AVs and the associated uncertainty—will change considerably once these products become established on the market. Second, our current model does not take into account mixed traffic effects, that is, a different accident probability of AVs when meeting another AV as compared to meeting a human driver, such that the share of AVs on the street has an impact on the accident probability of these vehicles. Third, our assumption that in case of a successful innovation the new quality of the innovator is mainly determined by the value of a consumer-independent technological frontier strongly simplifies the structure of dynamic innovation competition and ignores path dependencies, which might for example result from the fact that producers profit from data they receive from their own models on the street when training the next generation of AV models. Finally, it would be interesting to extend our analysis to a broader range of strategies. For example, a mix between the timing and quality strategy, under which the producer in principle releases new models after a fixed time interval but delays the release if the quality gap between the previous and the current model is not sufficiently large, could be a profitable alternative to the prototypical strategies here. All these extensions could be integrated into the framework developed in this paper.

Data and Code Availability

The model has been implemented in *Julia* (Bezanson et al., 2017) using the *Agents.jl* package (Datseris, Vahdati, and DuBois, 2023). The code and the data used in this paper are open source and can be downloaded from GitHub: https://github.com/ETACE/av_market_model

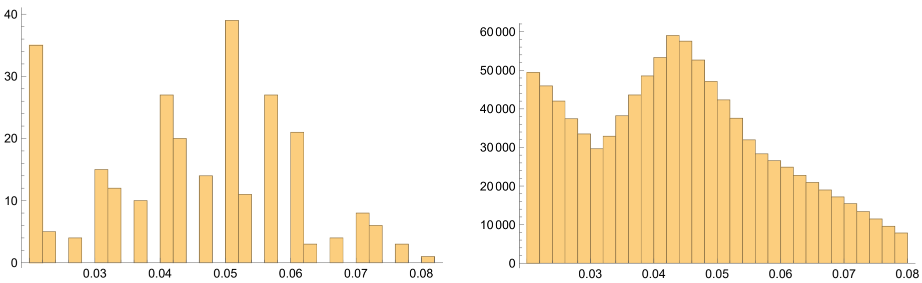
Appendix A Kernel Density Estimation

For each of the agent-specific parameters calibrated using the empirical survey, Figures A.1 to A.7 show the distribution of the respective parameter in the survey as well as the distribution of the parameter values sampled from the kernel density estimation (KDE).



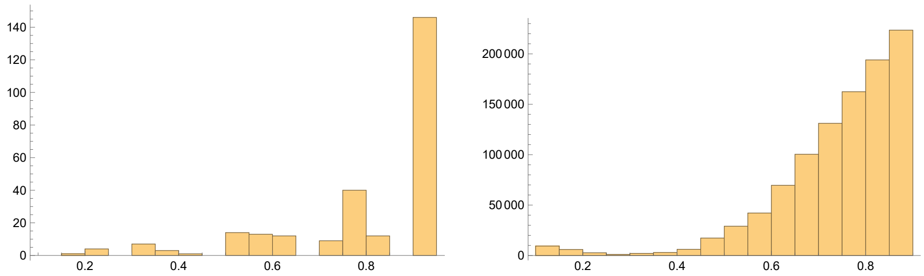
(a) *(b)*

Figure A.1
Distribution of minimum performance threshold $q_i^{\min}$ from (a) empirical survey and (b) sample drawn from KDE.



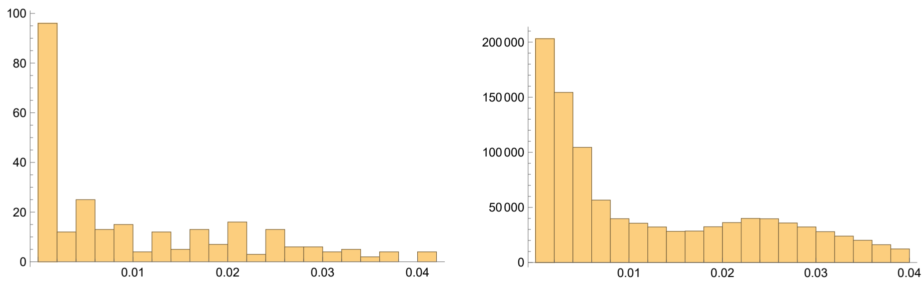
(a) *(b)*

Figure A.2
Distribution of maximum probability of accident threshold $p_i^{\max}$ from (a) empirical survey and (b) sample drawn from KDE.



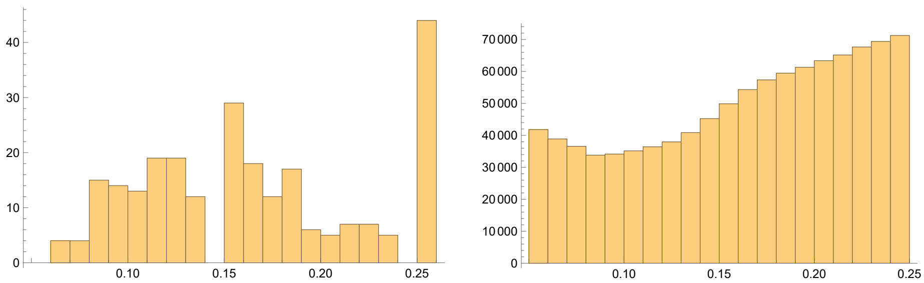
(a) *(b)*

Figure A.3
Distribution of probability threshold θ_i from (a) empirical survey and (b) sample drawn from KDE.



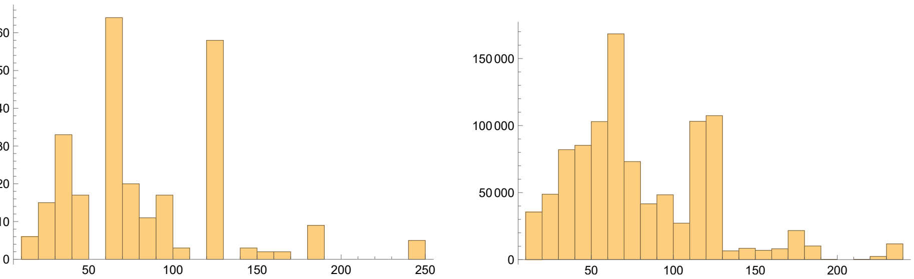
(a) *(b)*

Figure A.4
Distribution of probability to communicate ϕ_i^{talk} from (a) empirical survey and (b) sample drawn from KDE.



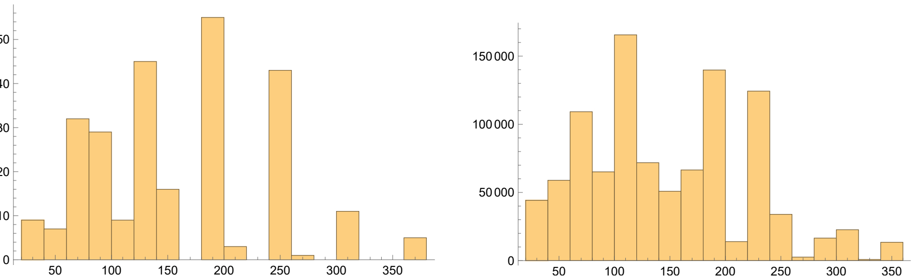
(a) *(b)*

Figure A.5
Distribution of communication noise σ_i^{comm} from (a) empirical survey and (b) sample drawn from KDE.



(a) *(b)*

Figure A.6
Distribution of minimum vehicle lifetime $v_i^{\min}$ from (a) empirical survey and (b) sample drawn from KDE.



(a) *(b)*

Figure A.7
Distribution of maximum vehicle lifetime $v_i^{\max}$ from (a) empirical survey and (b) sample drawn from KDE.

Appendix B Bayesian Learning

Bayesian learning is a statistical framework used in economics to model how agents update their beliefs and make decisions in an uncertain world. It is based on Bayes' rule, which provides a method for updating prior beliefs in light of new information. In Bayesian learning, prior beliefs are represented by a probability distribution and updated using Bayes' rule whenever new data becomes available. Following Baley and Veldkamp (2023), we assume that beliefs are normally distributed. Let $\omega \sim \mathcal{N}(\mu_\omega, \sigma_\omega)$ denote an agent's prior belief about a certain AV's property. In this case, the agent believes that the mean value of the property is μ_ω and σ_ω reflects how uncertain the agent is with respect to the value of this property. Whenever the agent receives a new (noisy) signal $s = \omega + \eta$, $\eta \sim \mathcal{N}(0, \sigma_s)$ about the property, she updates her belief by calculating a new mean as

$$\hat{\mu}_\omega = \frac{\frac{1}{\sigma_\omega}\mu_\omega + \frac{1}{\sigma s}s}{\frac{1}{\sigma_\omega} + \frac{1}{\sigma s}} \tag{A.1}$$

and a new variance as

$$\hat{\sigma}_\omega = \frac{1}{\frac{1}{\sigma_\omega} + \frac{1}{\sigma s}}. \tag{A.2}$$

Our assumption that both the prior belief and the signal are normally distributed imply by standard application of Bayes' rule that also the posterior belief is again normally distributed. The updated belief $\hat{\omega} \sim \mathcal{N}(\hat{\mu}_\omega, \hat{\sigma}_\omega)$ becomes the new prior and may again be updated if the agent receives another signal about the AV's property.

Appendix C Parameterization

Table C.1 provides the full list of parameters and their respective values in the baseline simulation runs. The parameters related to the technology have been calibrated such, that they result in a reasonable share of AV adapting consumers for the baseline during the time frame under consideration. Most of the consumer-specific parameters have been set using the results from a survey on German car owners. The remaining parameters have been chosen in a way to reflect empirical evidence whenever possible.

Table C.1
List of parameters.

Symbol	**Description**	**Value**
General		
T	number of iterations in months	700
N	number of AV producers	2
M	number of consumers	10 000
p_{CV}	CV accident probability (for reference)	0.05
Technology and AV producers		
$q^{-\infty}$	asymptotic minimum AV performance	0.0
q^{∞}	asymptotic maximum AV performance	1.0
q^{shape}	shape parameter for the performance curve	0.02
q^{shift}	shift parameter for the performance curve	300
$p^{-\infty}$	asymptotic maximum monthly AV probability of accident	$\frac{0.1}{12}$

Continued on next page

Table C.1 – continued from previous page – List of parameters

Symbol	Description	Value
p^{∞}	asymptotic minimum monthly AV probability of accident	$\frac{0.01}{12}$
p^{shape}	shape parameter for the probability of accident curve	0.02
p^{shift}	shift parameter for the probability of accident curve	300
λ^{q}	monthly innovation rate performance	0.05
λ^{p}	monthly innovation rate probability of accident	0.05
σ^{q}	innovation noise performance	0.05
σ^{p}	innovation noise probability of accident	0.0005
σ^{obs}	noise when observing probability of accident	0.0005
τ	interval between two AV releases when using the time strategy	96
Consumers		
$v_i^{\min}$	minimum vehicle lifetime	$[12, 240]$
$v_i^{\max}$	maximum vehicle lifetime	$[24, 360]$
$q_i^{\min}$	minimum performance threshold	$[0.05, 0.95]$
$p_i^{\max}$	maximum probability of accident threshold	$[0.02, 0.08]$
θ_i	minimum probability threshold	$[0.1, 0.9]$
ζ	monthly probability of considering CV/AV purchase	0.25
$\sigma_{\mathrm{ini}}^{\mathrm{q}}$	initial uncertainty w.r.t. performance	0.25
$\sigma_{\mathrm{ini}}^{\mathrm{p}}$	initial uncertainty w.r.t. probability of accident	0.0025
$g^{\mathrm{q}}(d)$	function to calculate initial uncertainty about performance	$\frac{1}{1+\exp(50d-0.1)}$
$g^{\mathrm{p}}(d)$	function to calculate initial uncertainty about probability of accident	$\frac{1}{1+\exp(50000d-0.0001)}$
ϕ^{use}	monthly probability to receive performance signal from AV usage	0.2
σ^{use}	noise in performance signal	0.1
ϕ_i^{talk}	monthly probability to communicate with friend	$[0.0, 0.04]$
σ_i^{comm}	communication noise	$[0.05, 0.25]$
ϕ^{media}	monthly probability to access information about AVs on media	0.1
Social network (euclidian Barabasi-Albert)		
n^{link}	number of new links per vertex	3
α	spacial exponent	-5.0
β	clustering exponent	1.0

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