Is the Time Ripe? How the Value of Waiting and Incentives Affect Users' Switching Behaviors for Smart Home Devices

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Abstract

Product-related and market-related uncertainties often cause users to defer from switching to new IT devices. There is a value of waiting (VoW) for users because waiting allows them to collect more information. At the same time, many IT switching decisions are increasingly complex due to increased connectivity and the resulting interdependencies between jointly used devices. Therefore, switching decisions for connected devices not only need to consider the new device in isolation, but must also account for the potential benefits from internally or externally connecting the device with other devices. Although crucial for users and providers alike, existing models cannot explain whether and when users switch in such connected environments.

We focus on connected Smart Home Devices (SHDs) and simulate users' actual switching timing based on a real options model which combines switching and deferral concepts in a context-specific setting. We examine how Smart Home Network (SHN) density influences switching and how providers can use incentives to accelerate switching to foster product diffusion. The findings show an accelerating effect of connectivity and a deferring effect of uncertainty on actual switching timing. We also learn that SHD providers should focus more on immediate than on delayed incentives to promote product diffusion, since the latter can also have undesired effects. Interestingly, external connectivity has almost no influence on decision timing in scenarios with highly dense SHNs, leading to further key implications for SHD providers.

Keywords: Real options approach, Value of waiting, Smart Home Devices, Incentive schemes, Private users.
JEL-Classification: *C63, D81, G11, O33.*

1 Introduction

Rapid technological progress is found in many areas and new generations of IT devices are frequently introduced. Consumers may therefore need to constantly assess whether they wish to switch to a new generation of IT devices. Finding the right time to switch is not easy, since the new device's capabilities and the user's ability to exploit them are often uncertain (Kim and Kankanhalli 2009). Switching too early can waste money and time (e.g. if a device does not work as intended), while switching too late may mean missing out on potential new benefits (Kauffman and Li 2005). This decision has become even more complex as many devices nowadays provide connectivity to other devices, promising to generate a higher utility when used jointly.

In this paper, we use *Smart Home Devices* (SHDs) as an example. These IT-enriched household devices (e.g., smart thermostats, locks or even washing machines powered by solar panels) integrate physical, sensory, and digital components into single products and are either connected to each other or with other IT devices (e.g., smartphones or tablets) in a *Smart Home Network* (SHN). By connecting compatible SHDs in an SHN, their functional ranges can be extended, bringing together intelligent devices from various application fields with different primary usage purposes (Kuebel and Zarnekow 2015; Rijsdijk and Hultink 2009). Using Internet-based connections, certain SHDs also allow for interactions with other users' devices (Aldrich 2003). We refer to these two scenarios as *internal* respectively *external connectivity*. In both cases, the utility for the focal users can increase if their SHDs are not merely used in isolation, but are instead connected with other internal or external SHDs.

Previous approaches have used the *value of waiting* (VoW) concept to explain switching decisions. It is based on the assumption that additional time provides users with more information about a new device's functionality and the likelihood of its market success (Dong and Saha 1998; Kauffman and Kumar 2008). However, these approaches have important shortcomings in the dynamic contexts of connected environments: First, they only take users' technological status quo into account without considering potential ideal switching times in the future (Fan and Suh 2014; Ranganathan et al. 2006; Zhang et al. 2009). Second, they approach users' utilities from a perspective that treats devices in isolation, i.e. they fail to account for the devices' connectivity as well as users' current and future tendencies to generate higher utility by using devices jointly with others. This is not only a major theoretical research gap, it is also of high relevance for providers of connected devices who consider incentives to foster users' switching decisions.

We interpret users' possibility to switch to new devices as a real option: users have the opportunity, but not the obligation, to select new SHDs and to substitute incumbent ones. Users can also defer the decision until a certain point in time. Although being a major determinant for whether switching takes place and for designing incentive schemes to foster switching, very few approaches have focused on the utility of deferring switching decisions (Henseler and Roemer 2013). We assess this utility in this work by interpreting the value of a particular option as a representation of the VoW. We comprehensively account for connectivity between devices and consider the development of uncertainty in intertemporal decisions by introducing a dynamic perspective. To do so, we develop a combined deferral and switching option (Kauffman and Li 2005; Kumar 1996; Loraas and Wolfe 2006), extend it with incentive schemes, and use least square Monte Carlo (LSM) simulation to calculate the value of this specific option – the VoW.

Altogether, we demonstrate that option theory is a natural tool to model user switching decisions for new technologies and to derive the VoW as well as the actual time to switch for scenarios of substantial interdependencies between devices. We also show how changes in SHN density and in the number of external connections alter the VoW and the actual point in time to switch, and analyze the impact of one-off and repeated incentives to foster switching.

We contribute to the literature by presenting a novel approach that employs the VoW concept as an explanation for deferred decisions in private users' technology management in environments that are characterized by connectivity-driven uncertainty. Taking the example of SHNs, our model explains the impact of uncertainty reduction and timing aspects as relevant factors in switching decisions. Regarding future research, our procedure to adapt models to critical decision semantics can also be used for other ROAs in the private user context. For SHD providers, we provide a better understanding of the roles of connectivity and the VoW in their customers' switching decisions. We also examine the impact of incentives on actual timing in different scenarios, which can help providers in the configuration of incentive schemes and enhance the diffusion of their products.

The remainder of this paper is organized as follows: In Section 2, we present the conceptual foundations of our work. Section 3 develops our enhanced real options approach. In Section 4, we derive solutions for the option values and actual switching timing and perform experimental simulations. In Section 5, we discuss the results and provide a sensitivity analysis to show the robustness of our results. We close with theoretical and practical implications as well as an outlook on future research in Section 6.

2 Conceptual Foundation

2.1 Application of Real Options to Switching Behavior

At any point in time, users have the opportunity, but not the obligation to switch. This is congruent with real options, which are defined by the right to take a certain future action or not. Therefore, the decision to switch to new SHDs embeds a switching option and a deferral option. This implies that we can build our switching model on the basis of established switching option models (e.g. Margrabe 1978), which address the exchange of financial assets. The switching option represents the combination of quitting the incumbent device (*put option*) and using the new one instead (*call option*). The option to defer provides users with more flexibility, since they have the opportunity to delay the decision until more information is collected (Saya et al. 2010). This corresponds to a *wait-and-see* strategy and constitutes the real option's time value, as it can reduce uncertainties about the de facto value of the option underlying (Benaroch 2002). To determine a specific option value, Black and Scholes (1973), and for switching options especially Margrabe (1978), have derived the fundamental equations, which we will take as a basis for our real option model. The basic option models have in common that they focus on uncertainty as a main driver in decision making. This allows linking the different concepts of the real option approach (ROA) and the private user perspective of the VoW that are characteristic of decisions in the field of SHDs.

The decision to switch requires private users to invest in a new SHD. In some sense, users' decisions are comparable to managers' decisions on IT investments in the organizational context. In the latter context, the ROA has already been shown to improve decision-making and help understand the role of minimizing uncertainty while waiting (Janney and Dess 2004). Dependencies between incumbent and new devices and software are important for various decision assessments; for instance, when firms seek to invest in new software platforms (Taudes et al. 2000). Such interactions are also relevant for SHNs, where the decision to switch to new SHDs depends on their compatibility to other connectable devices that users already possess.

To date, previous works that applied ROAs to technology investments have mainly focused on the valuation of investments from a company perspective. For instance, many studies emphasize the role of option value calculations as ways for managers' risk management to justify IT investment decisions (Dos Santos 1991; Harmantzis and Tanguturi 2007; Heinrich et al. 2011). Other research has used option models to derive optimal timing strategies for corporate technology selection decisions (Ji 2010; Kauffman and Li 2005; Sollars and Tuluca 2012). However, what has not yet received sufficient research attention, is the application of ROA to the private user context.

For the application of ROA, it is important that (at least) partial investment irreversibility and uncertain utility gains hold true, otherwise users could reverse an investment without monetary loss when new information becomes available or there is no new information becoming available, making immediate decisions equally good as delayed ones (Adner and Levinthal 2004; Burger-Helmchen 2007). However, the main challenge when transferring option theory to tangible, non-financial problems is to account for the assumptions of the financial models they were originally developed for. Whenever relaxations of these assumptions are necessary, we need to enhance the original models. Since option valuation models consider market risks, but more or less ignore project-specific risks (Diepold et al. 2009), we must reflect on the product-related uncertainties of SHDs in the valuation of the underlying asset. To overcome the lack of a perfect market, we must use valuation procedures that can integrate SHD related connectivity effects, consider users' expectations, and simulate the valuation development (Ullrich 2013). We apply simulations, such as the LSM approach, to allow for flexible option exercising and to identify the right timing to switch SHDs, while preserving the same basis as for the original option valuation models (Benaroch et al. 2007; Schwartz and Zozaya-Gorostiza 2003; Ullrich 2013). Finally, as noted, owing to their comprehensive connectivity features, the valuation of

SHDs is subject to connectivity effects, which emerge through either connecting different SHDs of one user (internal connectivity), or when users connect their SHDs with those of other users (external connectivity). We therefore extend existing views on network effects[1] to account for both internal and external connectivity as part of the valuation process.

When accounting for the specifics of SHDs, analyzing switching decisions would not be possible with either classical adoption models (such as the Technology Acceptance Model, Davis 1989), or theories on the diffusion of innovation (such as Rogers 2010). Theories on the diffusion of innovation often take on a market-perspective and classify users based on the time when they adopt an innovation. While we acknowledge that diffusion on a large scale is composed of several individual level decisions, adoption is different from switching in the way that, for the latter, a similar precedent technology is currently used, which resembles the basis for users' assessment of the potential of the new technology. By contrast, adoption models merely assess determinants of new technologies without taking the users' current technologies into account. Likewise, other dedicated switching models, such as the push-pull-mooring framework, do not usually account for factors such as connectivity, which are crucial for smart home technologies. Furthermore, such models only offer a static perspective, which does not account for the specific time of switching and the remaining usage time of the current technology.

2.2 Incentives to Influence Users' Switching Decisions

Ways to convince users to switch faster to their technology are of great interest for SHD providers, especially since a rapidly growing installed base can help them to achieve market leadership. While the VoW generally restricts the further diffusion, an explicit reduction of the VoW can accelerate user switching and let providers exploit the advantages of early market entries. One way for providers to reduce the VoW is to use monetary incentives.

Incentives and their function related to technology diffusion play a large role in many disciplines, such as management, organizational behavior, marketing, and computer science (Wymer

[1] Note that network effects usually assume a focal user's utility to be dependent on the diffusion or usage of the same or similar technologies by others, whereas for internal connectivity it is purely the focal user's decision whether to establish a physical connection between their devices.

and Regan 2005). They are differentiated concerning reward type and reward timing. For example, loyalty programs are used in cooperation with different companies. Providers can pay rewards immediately or can delay them (Rothschild and Gaidis 1981; Yi and Jeon 2003). Firms can use one-off subsidies and price discounts to stimulate switching to new devices, but they can also offer repeated rewards to bind users to a device after its purchase.

Incentives have an immediate positive effect on perceptions and serve as additional information in later evaluation considerations, which further increases the perceived value in the long run (Naylor et al. 2006). Besides this utility effect, incentives can reduce users' motivations to collect and recall product information and consider them in the decision process, so that waiting to gain information becomes less relevant (Aydinli et al. 2014). In consequence, incentives shorten waiting durations in users' switching decisions (Jørgensen and Zaccour 1999; Lin and Huang 2014), by increasing the utility of new devices and therefore also increasing the likelihood of switching (Andrews et al. 2010; Dodson et al. 1978).

Because of the considerable interdependencies between different devices and the resulting uncertainty concerning devices' utility, the case of SHDs is more complex than for scenarios where products and related switching decisions can be treated in isolation. Hence, it is not intuitively clear which incentives can be used to promote switching and what their effects are. We compare an incentive scheme consisting of an immediate, one-off reward that immediately reduces switching costs to new SHDs with a scheme of delayed repeated rewards that seeks to bind users in the long run.

3 Real Option Model Development

3.1 Decision Scenario and Model Derivation

We develop a real option model that represents end-users' VoW derived from the possibility to defer a switching decision to a future point in time. Our specific decision situation focuses on SHNs, in which users have the possibility to switch from the incumbent SHD (SHD1) to a new one (SHD2). Both SHD 1 and SHD 2 fulfill the same stand-alone functionalities, but the new one offers more opportunities to connect it with other SHDs of the focal user or an external SHN. For example, while the current smart thermostats already offer to communicate electronically with other thermostats in the same or another room and while they can automatically adjust the power of the main heating, the new generation of thermostats also offers convenient control access from any compatible smartphone or tablet.

Users' switching decisions are based on their SHD valuations; they build expectations about the utility they will receive if they switch and integrate the new SHD into their SHN ($E(U_2)$). They also build expectations about the utility they will receive from the incumbent SHD if they do not replace it ($E(U_1)$). Both expected utilities relate to the entire usage period, from taking the decision whether or not to switch (D_t), to the uncertain point in time when SHD1 or SHD2 are no longer usable (D_T); for instance, owing to technological obsolescence.

We interpret this decision scenario as private users' real option to defer switching because it is possible to replace SHD1 with SHD2. However, it is also possible to defer this decision until users possess sufficient information to take a deliberate decision, although there is no immediate need for users to switch as they can further use their incumbent SHD. The real option begins with the market entry of SHD2 (t_0) and ends with the finite expiration date (T), which is necessary since neither SHD1 nor SHD2 can be used forever. Therefore, in contrast to perpetual real options with an infinite horizon (Wong 2007; Zhang and Guo 2004), we interpret T as the point in time at which a future SHD generation enters the market. Then, SHD2 is no longer available in the present form because the provider of SHD2 stops selling it and introduces an entirely new SHD or changes important properties of SHD2, also rendering it effectively a new device. For instance, incentives to switch to SHD2 are dropped or related services are altered or discontinued. This decision scenario is illustrated in Figure 1.

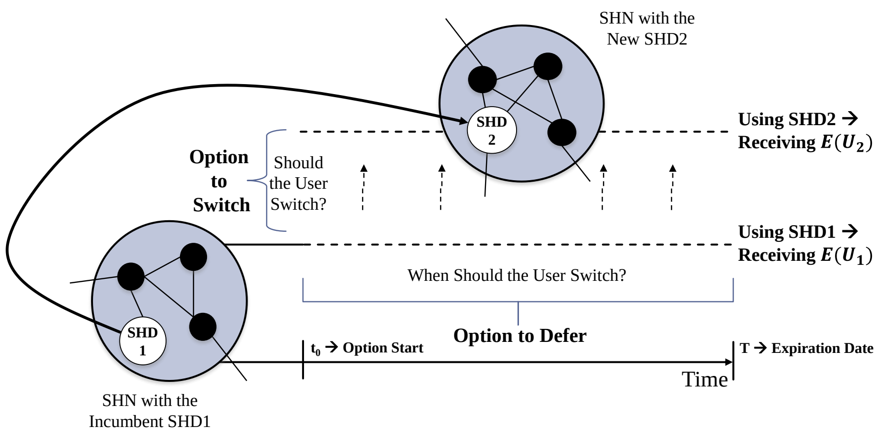

Figure 1. Decision Scenario: Option to Defer Switching SHDs

To handle the described semantics of the decision scenario, we first need a valuation for the option underlying (here, the SHD) that represents all relevant utilities concerning internal and external connectivity. Second, to account for real option modeling, we build on parameters of existing models that either address individuals' private switching behaviors (Haenlein et al. 2006; Henseler and Roemer 2013) or consider the value in deferring the selection of new technologies, but in corporate contexts (Benaroch and Kauffman 1999; Harmantzis and Tanguturi 2007). We combine the relevant elements concerning individual decisions on switching – switching costs and individual utility functions – and deferring – exercising and waiting costs – within the basic switching option model of Margrabe (1978). We therefore use the basic elements of the latter: comparisons between two different exercise prices of two different assets and a variance greater than zero for the difference between the development of asset prices (Margrabe 1978). Third, we integrate incentives, determine adequate and context-specific development processes for users' expectations while waiting, and implement the trade-off between deferral costs of switching too late and exercising costs of switching too early.

3.2 Determining the Option Underlying

To formalize an appropriate option underlying, we take a utility function approach. As noted, SHDs allow users to connect their "pure" IT devices with household devices as well as establish connections among their SHDs, both of which can increase SHDs' functionalities (Kuebel and Zarnekow 2015; Mennicken et al. 2014). In addition, the connections can be either within a user's SHN (internal connectivity), but also beyond (external connectivity). For instance, in the case of smartphones, there can be internal connections to other SHDs, such as smart TVs, but also exogenous connections to other users via communication applications. The former connectivity type leads to a super-additive utility in SHD valuation that users can internalize independent of other users' decisions. Therefore, the total utility (U) of an SHD has three components: first, a stand-alone utility from basic functionalities (A), for instance, a smartphone's alarm application; second, a connectivity-related utility (CV) emerging in connections between SHDs; third, a network-related utility (NV) for connections to other users (Berger et al. 2016; Matutes and Regibeau 1996). We therefore derive for SHD j

$$U_j = A_j + NV(b_j, N_j) + CV(c_j, DUC_j, H_j), \quad (1)$$

where $A_j, b_j, c_j > 0 \wedge N_j, H_j \in \mathbb{N} \wedge DUC_j \in [0, 1]$. Thereby, N_j denotes the exogenous network size, and b_j the external network valuation factor. Further, H_j denotes the number of SHDs in a private network, c_j the connectivity valuation factor, and DUC_j the degree of utilized connectivity (that is, SHN density related to j).

Users cannot fully predict the future development of the different utility elements of SHD valuation. They face uncertainties concerning connectivity effects, which influence NV, as well as uncertainties concerning the diffusion of the standard and compatibility to other devices, which influence CV. Owing to these unpredictable risks, we use individuals' perceived expected utilities to represent the option underlying. As the valuation includes all future usage periods of an SHD, we take the discounted expected utilities into account. That is, $E(U_1)$ reflects the expected net utility gains from using SHD1 in the future and $E(U_2)$ reflects the expected net utility gains from using SHD2 in the future, both calculated at the time when users take the decision whether or not to switch.

Since significant uncertainties accompany the expected utilities, it is possible to extend these utilities by the option premium w, in other words the VoW (Trigeorgis 1996). Therefore, we derive the total utility of a user's investment in an SHD j ($EU_{j,Total}$) by

$$EU_{j,Total} = E(U_j) + w = E\left(A_j\right) + E\left(NV(b_j, N_j)\right) + E(CV(c_j, DUC_j, H)) + w. \quad (2)$$

We assume that users evaluate both the incumbent device and the new alternative accordingly. If users switch, $E(U_2) + w$ constitutes the actual switching value. If they do not switch and therefore do not exercise the option ($w = 0$), users derive $E(U_1)$ for using SHD1 in the future. We will specify the functional forms of Equation 1 and 2 in detail when we describe the data generation process.

3.3 New Real Option Model Specification

To specify our new option model, we use a stochastic process of users' expected changes in $E(U_j)$ while they wait. Figure 2 presents an illustration of an exemplary development process of expected utility. It mainly shows the expected net utility of SHDj during the option duration respectively until the option is exercised at time t^* (bold line: until option is exercised, dotted line: after exercise). Note that in addition to the development process from t_0 to t^* (as depicted, if the option is exercised at all) also the development processes during the entire option duration (t_0 to T, not depicted after t^*) are relevant for the switching decision. The development processes in the usage period (D_t to D_T) are not considered in the decision, because the decision is already made. However, they are reflected in users' expected utilities $E(U_1)$ and $E(U_2)$.

To ensure context-adequacy, we differentiate between the development of $E(A_j + CV(c_j, DUC_j, H_j)) = E_{Aj} + E_{CVj} = E_{ACVj}$ and of $E(NV(b_j, N_j)) = E_{NVj}$.

For the development of changes in E_{ACVj}, we assume a geometric Brownian motion as a typical stochastic differential equation type to model uncertainty in option valuation, one that is frequently used for new technologies that enable new application fields (Carr 1995; Taudes et al. 2000). We argue for an upward trend in expectations, since users will obtain information about how to exploit all functionalities of SHD2 and how to use it with other SHDs in their SHNs. Moreover, owing to habituation, they expect to increasingly exploit the utility of SHD1, also confirming an upward trend. Therefore, we derive

$$dE_{ACVj} = E_{ACVj}\,[(\mu_{E_{ACVj}} - \delta_{E_{ACVj}})dt + \sigma_{E_{ACVj}} dz_{E_{ACVj}}]\;(j = 1, 2), \tag{3}$$

with $\mu_{E_{ACVj}}$ as the expected changes growth rate and the standard deviation $\sigma_{E_{ACVj}}$ as its volatility. In general, $\delta_{E_{ACVj}}$ represents dividend yields (the deferral costs of waiting or the exercising costs of switching), and $dz_{E(U_j)}$ the increment of a standard Wiener process at time t with $dz_{E(U_j)} \sim N(0, dt)$ (Carr 1995; Harmantzis and Tanguturi 2007; Margrabe 1978).

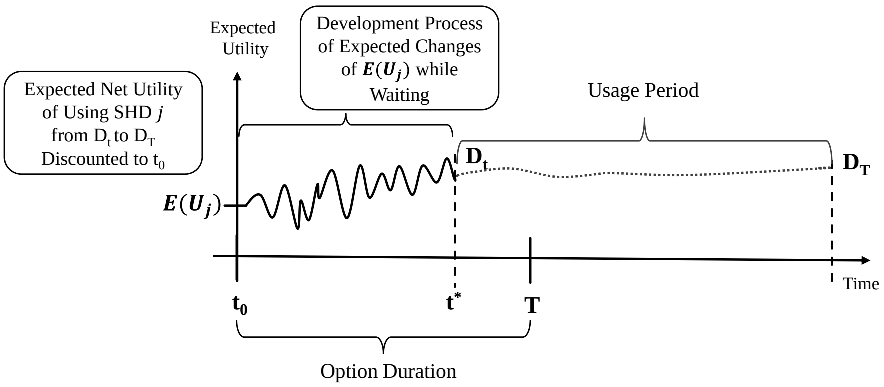

Figure 2. Exemplary Development Process of Expected Changes of $E(U_j)$

For the development of changes in E_{NVj}, we assume a jump diffusion process. Such discontinuous movements occur when new information supports a re-evaluation of the option underlying (Kou 2002; Merton 1976). Jump diffusions can capture external connectivity effects. For instance, users will decrease their expectations on an SHD's perceived utility if they obtain information predicting that a sufficient installed base will not be reached (Kauffman and Kumar 2008). A jump process dq can be represented by

$$dq = \begin{matrix} \nearrow 0, with\ Pr_{Jump} = 1 - \lambda dt \\ \searrow 1, with\ Pr_{Jump} = \qquad \lambda dt \end{matrix}, \tag{4}$$

where λ is the mean number of jumps per unit time and Pr_{Jump} is the probability of a jump (Kauffman and Kumar 2008; Merton 1976). We formulate a related Poisson-driven process:

$$dE_{NVj} = E_{NVj}\ [(\mu_{E_{NVj}} - \delta_{E_{NVj}} - \lambda\kappa)dt + \sigma_{E_{NVj}} dz_{E_{NVj}} + dq]\ (j = 1, 2), \tag{5}$$

with $\mu_{E_{NVj}}$ as the expected changes growth rate, $\sigma_{E_{NVj}}$ as its volatility and $\kappa \equiv E(Y - 1)$, where $(Y - 1)$ is a random variable that captures the percentage change in the expected network utility (Kauffman and Kumar 2008; Merton 1976). We assume dq and $dz_{E_{NVj}}$ to be independent. Equation 5 reflects continuously varying expected user numbers. Discrete jumps will occur randomly, reflecting an SHD's expected success or failure (Kauffman and Kumar 2008).

Our model uses the fundamental equations of the basic switching option model of Margrabe (1978) with respect to the existence of two different exercise prices. However, we integrate switching costs and incentives from the individual user perspective. We further concretize waiting and exercising costs to account for deferral in our decision situation. Therefore, we let the option's exercise price be the sum of $E(U_1)$, which is lost if users switch, and the difference between additional switching costs K (lump sum) and the provider's immediate, one-off incentive I, i. e., $E(U_1) + (K - I)$. Additional switching costs exist because users need, for instance, to invest extra time in learning to use the new SHD or need to buy new complementary products for the SHN (Burnham et al. 2003). SHD providers can directly reduce these costs by offering a one-off reward to a potential customer (Corbo and Vorobeychik 2009). We implement a deferral cost rate γ on SHD2's utility and an exercise cost rate r on SHD1's utility, analog to dividend yields. Therefore, we can consider the trade-off between switching too early or using the new device too late, which justifies why finding the right timing to switch is both useful and necessary (Benaroch and Kauffman 1999; Harmantzis and Tanguturi 2007). Deferring provides users with the opportunity to gather more information, but they cannot use the new SHD while waiting and, therefore, do not profit from its utility during that time. SHD providers can influence the deferral costs by offering repeated delayed incentives; that is, the incentives are provided throughout the whole usage period. For instance, they can offer free monthly updates and additional applications that enhance the functionalities of users' SHDs (Corbo and Vorobeychik 2009). Waiting to switch increases the deferral costs since these rewards cannot be obtained. We assume the incentives to be a multiplicative factor in the form of $(1 + i)$ (with $i \geq 0$) so that the deferral costs are $\gamma \cdot (1 + i)$.

Implementing the described modifications, we are able to formalize our real option model concerning the individual user perspective and the waiting perspective. The initial equation for the option value (w) is given by

$$w(E(U_2), E(U_1), K, I, T) = \max(0, E(U_2) - (E(U_1) + (K - I))). \quad (6)$$

3.4 Solution Approach

For now, we ignore that the expected changes of E_{NVj} are modeled with a jump diffusion process and assume that $E(U_j)$ follows the Geometric Brownian Motion in all expected utility elements. We obtain a closed form solution for the value of our option type by

$$w_{BS}(E(U_2), E(U_1), K, I, T) = E(U_2)\, e^{-(1+i)\gamma T} N(d_1) - (E(U_1) + (K - I)) e^{-rT} N(d_2),$$

with $d_1 = \frac{\ln(E(U_2)\,/(E(U_1)+(K-I)))+(0.5\sigma^2-(1+i)\gamma\,+\,r)T}{\sigma\sqrt{T}}$, and $d_2 = d_1 - \sigma\sqrt{T}$. (7)

Here, σ denotes the standard deviation of the expected change rate on $E(U_1)$ and $E(U_2)$, and $N(*)$ the standard normal distribution function (Black and Scholes 1973; Margrabe 1978; McDonald and Siegel 1986). Let us now define a random variable X_n, which has the same distribution as the product of n i.i.d. random variables, of which each is identically distributed as the random variable $(Y - 1)$. Further, we define E_n to be the expectation operator of X_n (Merton 1976). We can now derive from Equation 7 the option value while accounting for jumps by

$$w(E(U_2)\,, E(U_1)\,, K, I, T) = \sum_{n=0}^{\infty} \frac{e^{-\lambda T}(\lambda T)^n}{n!} \left[E_n\left\{w_{BS}\left(E(U_2)X_n e^{-\lambda\kappa T}\,, E(U_1)\,, K, I, T\right)\right\}\right]. \quad (8)$$

Equation 8 is no closed-form solution. However, it allows us to approximate solutions reasonably well via LSM simulation (Kou 2002; Longstaff and Schwartz 2001; Merton 1976). Our real option model combines important modifications for the SHN context. The option underlying is based on the specific utility elements of SHDs and considers users' expected utility perceptions. Defining an appropriate underlying is indispensable to account for individual users and their switching behavior.

Further, technology investments, such as users' selection of SHDs, require the implementation of deferral costs and exercise costs to consider the related trade-offs (Benaroch and Kauffman 1999; Harmantzis and Tanguturi 2007). The incumbent device is not perfectly risk-free, but provides users with a comparably constant and well assessable utility. Therefore, we assume that $\gamma \cdot (1 + i) > r$.

The users can execute the option to defer switching on any given day within the option duration. There are no analytical closed-form solutions for such American-type options. Therefore, we need approximation processes (e.g., LSM simulations) to calculate the option value and users' switching timing (Benaroch and Kauffman 1999; Harmantzis and Tanguturi 2007; Longstaff and Schwartz 2001). Note that the calculated time to switch maximizes users' utility concerning uncertainties and expectations, which encourages them to actually switch (t^* denotes the actual switching timing). However, t^* is optimal only subject to the information available to users at a given point in time; hence, we refer to actual rather than optimal time to switch.

4 Solutions for Option Values and Actual Switching Timing

To derive solutions, we first determine variables and calculate the option underlying's expected utilities. Further, we define simulation paths by following our stochastic differential equations. Based on specific values and randomly generated data, we use the LSM simulation algorithm to derive the American-type values. We repeat several simulation runs and take the mean values of the VoW and t^* as the basis for sensitivity analyses on expiration dates and the volatility in expectations. Finally, we vary values for internal connectivity and external connectivity and compare different provider incentive schemes. Figure 3 gives an overview of the different steps to calculate the switching decision as well as on the parameters in the sensitivity analysis.

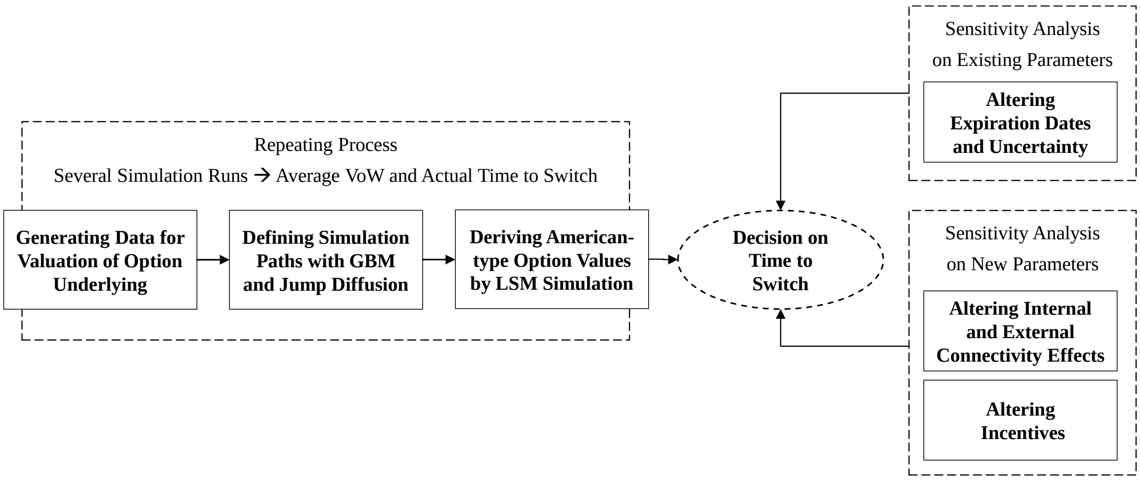

Figure 3. Simulation Procedures and Analyses

4.1 Data Generation Processes and Simulation Paths

We specify the expected utility functions (Equations 1 and 2) and their development in the usage period (D_t to D_T, as indicated in Figure 2). We divide the usage period into a certain number of time increments ddt ($ddt = \{0; 1; 2; 3; 4; 5\}$); that is, we assume a usage time of 5 years starting with the point in time when users decide whether to switch – t^* ($ddt = 0$). In this period, we assume that the internal and external network size develop from year to year following an epidemic network diffusion model (Geroski 2000). To calculate the future time path of the internal network size ($H_j(ddt)$), we derive

$$H_j(ddt) = \frac{H_{j,ex}}{[1-\phi e^{-\alpha H_{j,ex} ddt}]}, \text{ with } \phi = \frac{H_{j,ex} - H_j(ddt=0)}{H_j(ddt=0)}, \quad (9)$$

where $H_{j,ex}$ denotes the potential expected network size and α denotes a coefficient reflecting the scale by which the network integration of previous SHDs influences the usage of emerging SHDs. $H_j(ddt = 0) > 0$ must hold true (Geroski 2000). We propose that $H_{2,ex} > H_{1,ex}$ because the new SHD2 has greater connectivity possibilities than SHD1. Equivalently, to calculate the future time path of the external network size ($N_j(ddt)$), we derive

$$N_j(ddt) = \frac{N_{j,ex}}{[1-\phi e^{-\beta N_{j,ex} ddt}]}, \text{ with } \phi = \frac{N_{j,ex} - N_j(ddt=0)}{N_j(ddt=0)}, \quad (10)$$

where $N_{j,ex}$ denotes the potential expected network size and β is a coefficient reflecting the scale by which previous users influence new ones. $N_j(ddt = 0) > 0$ must hold true (Geroski 2000).[2] $N_{2,ex}$ is characterized by users' uncertainty: they do not know whether SHD2 will reach a considerable installed base, leading to a large external network size, or whether SHD2 will fail in the market and the number of possible external connections will decrease (Katz and Shapiro 1994). Therefore, we implement a failure rate f in the new SHD's potential external network size. SHD providers can decrease the probability of failure F by offering incentives. We obtain the following distribution rule for expected potential network sizes:

$$N_{2,ex} \begin{matrix} \nearrow > N_{1,ex}, with\ 1 - F(f, I, i) \\ \searrow < N_{1,ex}, with \quad\quad F(f, I, i) \end{matrix}, \quad (11)$$

where $F'(f) > 0$ and $F'(I)$, $F'(i) < 0$. To transfer internal and external network size into utilities, we assume that CV and NV for both SHDs follow curves with diminishing marginal utilities. We use ln-functions to reflect that a network size of at least 2 is needed to generate connections-related utility. CV and NV are calculated for ddt with related network sizes. We derive:

[2] The necessary conditions $H_j(ddt = 0) > 0$ and $N_j(ddt = 0) > 0$ are not problematic in our scenario, because an internal network already exists and because independently of SHD2's market success or failure in the long run, we can at least assume that some early adopters will use SHD2 already before it has seen strong market diffusion.

$$CV(c_j, DUC_j, H_{j,ddt}) = c_j \cdot DUC_j \cdot \ln(H_{j,ddt}); \tag{12}$$

$$NV(b_j, N_{j,ddt}) = b_j \cdot \ln\big(N_{j,ddt}\big). \tag{13}$$

We build the net present values discounting CV and NV to $ddt = 0$, representing the expected utilities E_{CVj} and E_{NVj}. To indicate that the basic functionalities of SHD2 are equal or better than SHD1, we take $E_{A1} = A_1$ as a fixed parameter, but assume that

$$E_{A2} = E_{A1} + s_2 \cdot \eta_2, \tag{14}$$

where $\eta_2 = [0; 1]$ is an uniformly distributed random number and $s_2 \in \mathbb{N}^+$ is a deviation factor accounting for how much SHD2 is expected to outperform SHD1 in stand-alone usage. Therefore, we can sum up E_{Aj}, E_{CVj} and E_{NVj} to derive $E(U_j)$ for SHD2 and SHD1.

The valuation factor c_j is taken as a random, multiplicative factor from a normal distribution. f, I, i, b_j and DUC_j are fixed parameters. We assume that $DUC_2 > DUC_1$ since we noted that the new SHD should be a superior alternative in terms of connectivity, making possible a denser private network. Since c_j, $N_{j,ex}$ and η_2 are all random variables, they reflect users' uncertainties relating to the different utility parts: users do not know for sure how much better the stand-alone functionalities in SHD2 are (η_2 in stand-alone utility); they do not know if they are able to exploit the additional utilities of better connectivity features in SHD2 (c_j in connectivity-related utility); they do not know whether SHD2 can reach a broad market diffusion ($N_{j,ex}$ in external network-related utility).

Next, we simulate the development processes of expected changes in $E(U_2)$ and $E(U_1)$ on 1000 paths ($NS = 1000$) and thereby prepare to apply the LSM algorithm. For this purpose, we define $T = 1$ as time to expiration and $NT = 365 \cdot T$ as the number of time intervals t. We assume that users could take their switching decisions in any time interval during the option duration. To derive the processed values of $E(U_2)_t$ and $E(U_1)_t$ for any time interval, we use $E(U_2)$ and $E(U_1)$ as starting points in the first time interval ($t = 1$) and iteratively add $dE(U_j) = dE_{ACVj,t} + dE_{NVj,t}$ for all other time intervals according to the Geometric Brownian Motion and the jump diffusion process (Equations 3 and 5). We set $\sigma_{E_{ACV2}} > \sigma_{E_{ACV1}}$ and $\sigma_{E_{NV2}} >$

$\sigma_{E_{NV_1}}$ to implement that, owing to related uncertainties, SHD2 is a more volatile alternative than SHD1 so that new information during the decision phase can have a stronger (positive or negative) effect on expected valuation changes. We simulate the expected changes for every path and derive two $NS \times NT$ simulation path matrices $\Theta_{E(U_1)}$ and $\Theta_{E(U_2)}$, where every row presents the expected development of the valuation of the option underlying while waiting (Appendix 1 shows the specific parameter values for our base case).

As we will describe in the next section, we use the generated data to calculate option values and actual timing via the LSM approach.

4.2 Calculating the Value of Waiting and the Actual Time to Switch

Longstaff and Schwartz (2001) formulate the following decision rule for LSM: at any incremental point of time in the expiration period, option owners exercise an American option if the immediate payoff of exercising is higher than the expected payoff from continuing to hold the option. Accordingly, the optimal exercise timing depends on the conditional expectation of option continuation payoffs. Therefore, we must estimate continuation values for every time interval from the cross-sectional information given in the simulation path matrices by using least square regressions. The fitted values represent expected continuation values, and we compare them with immediate exercising to identify the right exercise decision along each simulation path. We repeat the procedure recursively for every time interval to calculate the option value by discounting the net utility gains to the first time interval (Moreno and Navas 2003).

To apply the LSM algorithm, we build the utility gain matrix Ω for every simulation path by searching the positive differences between $\Theta_{E(U_2)}$ and $(\Theta_{E(U_1)} + (K - I))$ (K, I as scalars) and by setting 0 if differences are negative. This is necessary to adapt the approach to our combined option type. We derive:

$$\Omega = \max(\Theta_{E(U_2)} - (\Theta_{E(U_1)} + (K - I)), 0). \quad (15)$$

If the option is in the money at time interval $NT - 1$, users can decide between exercising immediately or continuing to hold the option until T. Let vector Z denote $E(U_2)$ at time interval $NT - 1$ for the in-the-money paths and Y denote the corresponding discounted utility gains at time interval NT if the option is not exercised. Analogous to Longstaff and Schwartz (2001), we regress Y on a constant and different nonlinear functions (Laguerre Polynomials) of Z. Therefore, we derive the estimated utility gains from option continuation conditional on $E(U_2)$ at time interval $NT-1$. If the value of immediate exercise is greater than the value from continuation, it is best to exercise the option, otherwise it is optimal to exercise later. We recursively repeat the procedure – least square regressions and value comparisons – until time interval 2 (Longstaff and Schwartz 2001; Moreno and Navas 2003). The result is an optimal time interval to exercise the option for every simulation path with the corresponding optimal utility gain $UG*$ taken from the utility gain matrix Ω. We discount all the optimal utility gains back to the starting date and derive the American-type option value w_{AM} with the discounted utility gains $\overline{UG}*$ as

$$w_{AM} = (\sum_i^{NS} \overline{UG}_i*)/NS. \quad (16)$$

The time to switch $t*$ (also referred to as actual timing) reported in the following is the average of the above-mentioned time intervals when the option is exercised over all paths. We also calculate the duration of waiting as the share of t^* to the total number of time intervals NT: $t^*_{perc} = t^*/NT$.

Finally, we repeat the process described, from calculating the valuation of the option underlying, to constructing the simulation path matrices, to using the LSM approach in 1000 simulation runs (creating 1000 paths each). The values reported in the following are means over all 1000 simulation runs[3]. We provide numerical solutions for users' VoW and indicate the actual timing for switching SHDs. In addition, Table 1 also presents the results for expected connectivity- and network-related utilities. The user actually switches after approximately 90 days, in other words, after 25% of the option duration. Further, the user positively values the opportunity to defer a decision, with a VoW of 21.09. The user's expected valuation for SHD2 ($E(U_2) =$

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[3] We performed all analyses with MATLAB R2014. We also calculated 95% confidence intervals for $t*$ *([86.01;93.81]) and w_{AM} ([20.39;21.78]).* The results indicated that 1000 simulation runs provide a stable basis for our analysis.

181.79) significantly exceeds the expected valuation of SHD1 ($E(U_1) = 146.07$), mainly because of the much better expected connectivity-related utility. We will use these values for comparisons and will observe how they alter in the sensitivity analysis.

Value of Waiting w_{AM}	Actual Timing t^*	Actual Waiting Duration t^*_{perc}	Option Underlying Valuation $E(U_2)$	$E(U_1)$	Expected Connectivity-related Utility E_{CV2}	E_{CV1}	Expected Network-related Utility E_{NV2}	E_{NV1}
21.09	89.91	24.63%	181.79	146.07	83.74	44.18	35.53	41.89

Table 1. Mean Simulation Results (Base Case)

4.3 Altering Expiration Dates and Volatilities

As stated in Section 3.3, our ROA cannot yet address two semantics of our decision scenario: First, an uncertain, but fixed expiration date T, and second, a decreasing uncertainty of the development of expected utilities while users wait. We handle both specifics by performing sensitivity analyses.

First, we vary T and simulate our VoW and actual timing for an option duration up to six years, i.e., $T = \{1; 2; 3; 4; 5; 6\}$, assuming that most current SHDs will no longer be used and must be replaced in case of longer periods. We run all five new simulations with the same seeds for the random number generator to ensure comparability.[4] The results for option value, actual timing and actual waiting duration are shown in Table 2. We find that altering the option duration has no significant influence on w_{AM} – the VoW. The value varies between 21.03 and 22.52. Users mostly value the fact that they have the possibility to wait, but how long they can defer a decision is less important. A longer period of possible waiting has a small effect on actual timing: even if the point in time to switch is later in absolute terms, users should switch earlier relative to the option duration. There is a tendency that actual timing in percent of the option duration is lower with higher T. This means that our base case with its shorter one year expiration date is slightly biased as it shows a longer (relative) actual waiting duration t^*_{perc} compared to longer option durations.

Expiration Date T		Value of Waiting w_{AM}	Actual Timing t^*	Actual Waiting Duration t^*_{perc}
Simulation Results (Mean Values, 1000 Simulation Runs, Varying T)				
(Base Case)	1	21.09	89.91	24.63%

[4] This process is repeated in all later sensitivity analyses: we ensure that every simulation for every parameter variation performs 1000 simulation runs and that every first, second, or n-th run uses the same number generator seeds.

2	22.52	137.95	18.90%
3	21.81	188.41	17.21%
4	22.13	243.51	16.68%
5	21.03	313.40	17.17%
6	22.14	314.57	14.36%

Table 2. Simulation Results for Varying Expiration Date T

Second, to show that the volatility of the expected changes should decrease during the option duration owing to more information, we vary $\sigma_{E_{ACV2}}$ and $\sigma_{E_{NV2}}$, which determine the development of the expected utilities of SHD2 during the option period. This is necessary because there are no appropriate processes that allow us to implement a decreasing volatility in our ROA, even if it should shrink owing to more information collected while users defer to switch. By altering volatilities, we learn how to interpret the results of our simulated model concerning users' uncertainty (Table 3). First, we vary $\sigma_{E_{ACV2}}$ and $\sigma_{E_{NV2}}$ simultaneously. Then, we vary only one of them and compare the findings. Increasing $\sigma_{E_{ACV2}}$ and $\sigma_{E_{NV2}}$ simultaneously raises the VoW from 21.09 to 39.10, and users will wait longer to take the switching decision, 46.01% of the option duration instead of 24.63%. The higher the uncertainty, the more users can profit from waiting so that w_{AM} increases and the better it is to defer switching. We can see from varying the volatilities separately that a higher uncertainty regarding the internal connectivity effects ($\sigma_{E_{ACV2}} = 0.5; \sigma_{E_{NV2}} = 0.05$) drives this effect more strongly than a higher uncertainty regarding the external effects ($\sigma_{E_{ACV2}} = 0.05; \sigma_{E_{NV2}} = 0.5$). Accordingly, if we start with the initial volatility and keep it constant, therefore failing to capture the actually decreasing volatility, the model overestimates volatility, and, therefore, we overestimate both actual timing and waiting duration. These effects are in line with the basic ROA assumptions and they provide further evidence that our developed model is still consistent with ROA theory.

Volatility Geometric Brownian Motion $\sigma_{E_{ACV2}}$	Volatility Jump Diffusion $\sigma_{E_{NV2}}$	Value of Waiting w_{AM}	Actual Timing $t*$	Actual Waiting Duration t^*_{perc}
Simulation Results (Mean Values, 1000 Simulation Runs, Varying $\sigma_{E_{ACVj}}$ and $\sigma_{E_{NVj}}$ together)				
(Base Case) 0.05	(Base Case) 0.05	21.09	89.91	24.63%
0.15	0.15	23.54	96.95	26.56%
0.25	0.25	27.46	119.57	32.76%
0.35	0.35	31.97	142.50	39.04%
0.5	0.5	39.10	167.93	46.01%
Simulation Results (Mean Values, 1000 Simulation Runs, Varying $\sigma_{E_{ACVj}}$ and $\sigma_{E_{NVj}}$ separately)				
0.5	0.05	37.79	163.13	44.69%

0.05	0.5	22.90	111.31	30.50%

Table 3. Simulation Results for Varying Volatilities $\sigma_{E_{ACV2}}$ and $\sigma_{E_{NV2}}$

4.4 Sensitivity Analysis on Internal and External Connectivity

Since the presence of internal and external connectivity and their interactions are particularly important for SHDs, we examine changes to internal connectivity (affecting E_{CVj}) and to the number of external connections (affecting E_{NVj}). Of interest are the changes to SHD2 when SHD1 remains unchanged. To concretize, we address two questions: first, what happens if the possibilities to connect SHD2 to the user's other devices are increased, i.e. increasing DUC_2? Second, how does varying the failure rate f, which influences the expected external network size (and therefore, external connectivity), affect the results? We analyze both of the variations for three distinct scenarios: first, all else being equal except for the critical variable; second, for a high-volatility scenario (using higher $\sigma_{E_{ACV2}}$ and $\sigma_{E_{NV2}}$); third, we vary DUC_2 in a scenario with a high failure rate and f in a scenario with a high SHN density to extract interaction effects.

First, we vary DUC_2 in steps of 0.05 between 0.5 and 0.9 (Figures 4a and 4b). We calculate the high-volatility scenario with $\sigma_{E_{ACV2}} = \sigma_{E_{NV2}} = 0.5$ and the high failure rate scenario with $f = 0.8$. We find that DUC_2 positively affects the VoW (Figure 4a) and that the actual time to switch is earlier if the connectivity of SHD2 is relatively higher compared to SHD1's connectivity (Figure 4b). This holds true for all scenarios. Increasing DUC_2 results in a greater E_{CV2} (from 83.74 to 150.73) in all cases, increases $[E(U_2) - E(U_1)]$ and reduces actual switching timing owing to higher unrealized utility gains. Independently of the value of DUC_2, a higher volatility increases the option value (confirming the sensitivity analysis regarding volatility in Section 4.3) and a higher failure rate reduces it. We observe that all real option values increase owing to the increase in connectivity. Users value the possibility to gain information about the additional connectivity features.

Further, we see that raising internal network connections is more effective when there are fewer external connections. In the base case, varying DUC_2 reduces actual timing (in %) by 21.67 percentage points (24.63% to 2.06%), while a reduction of 40.55 percentage points

(44.96% to 4.41%) is possible for $f = 0.8$. A higher E_{CV2} can rapidly outweigh decreased expected valuations regarding the external network, at least if users want to accelerate their switching decisions. Interestingly, in the high-volatility scenario, the resulting graph decreases much slower, compared to the other two scenarios. For instance, when increasing DUC_2 from 0.5 to 0.55 raises $[E(U_2) - E(U_1)]$ (from 35.94 to 44.37), the actual timing is reduced only by 0.9 percentage points from 43.42% to 42.53%, whereas the same connectivity change reduces actual timing by 5.71 and 9.65 percentage points in cases with lower volatility. Therefore, the effects of a better internal connectivity are hampered by the uncertainty about the viability of these effects.

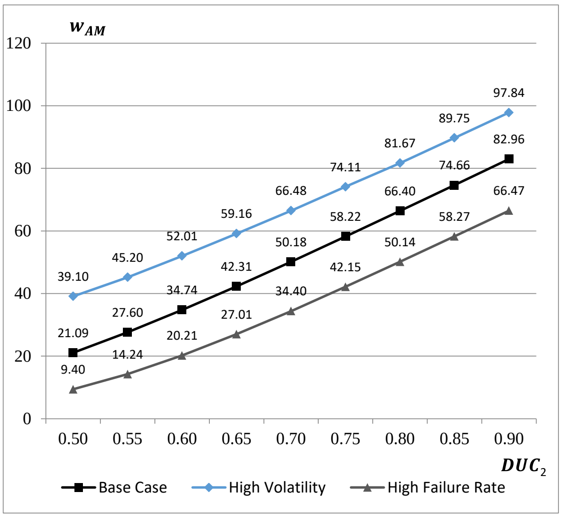

Figure 4a. Effects of Varying DUC on the VoW

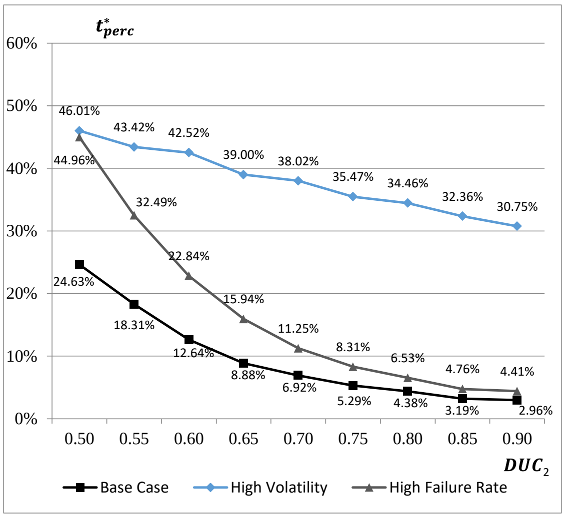

Figure 4b. Effects of Varying DUC on Actual Timing (%)

Next, we vary f in steps of 0.1 between 0.1 and 0.8 (Figures 5a and 5b). An increase in f reduces E_{NV2} since SHDs' market diffusion is expected to be subject to a higher failure rate. We calculate the high-volatility scenario again with $\sigma_{E_{ACV2}} = \sigma_{E_{NV2}} = 0.5$ and the high internal connectivity scenario with $DUC_2 = 0.9$. In all three scenarios, the reduction of external network connections results in a lower VoW; however, the option value level is sharply higher in the case of higher volatility and when SHD2 is more valuable owing to better internal connectivity (Figure 5a). The higher f, the longer users will wait with a switching decision. While this effect is present for every scenario, the extent of the effect differs substantially (Figure 5b). The relationship is strongest for the base case, where the actual timing increases from 9.55% to 44.96%. With a higher volatility, the actual timing increases only by 9.12 percentage points (from 26.03% to 35.15%), and the effect is much weaker. Interestingly, a higher volatility does not imply a generally later switching decision. At a failure rate of 0.6 and higher, the actual switching timing is earlier compared to the base case (for instance at $f = 0.8$, $t^*_{perc} = 35.15\%$ for the high volatility case compared to $t^*_{perc} = 44.96\%$ in the base case). Again, the higher uncertainty about utility effects, here due to external connectivity, hampers the impact of these utility effects.

Further, we find that in a high internal connectivity scenario, the influence of an increasing failure rate almost vanishes, and t^*_{perc} increases from 2.47% to 2.45%. This confirms our previous finding that a dense SHN accelerates switching decisions independently of the external connectivity effects. Even if E_{NV2} has an effect on the valuation of the option, it barely influences decision timing in the case of high internal connectivity.

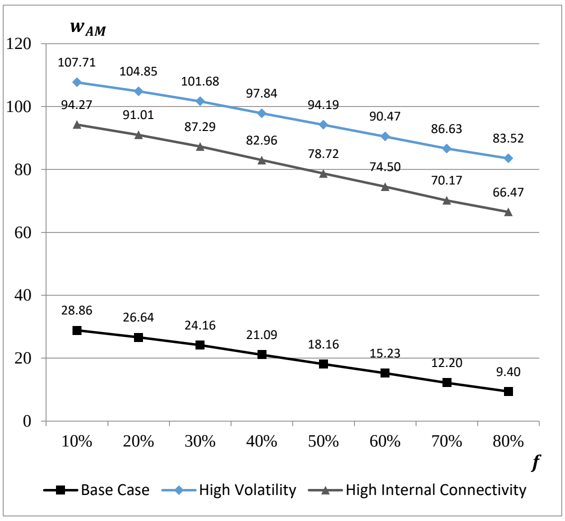

Figure 5a. Varying Failure Rates' Effects on VoW

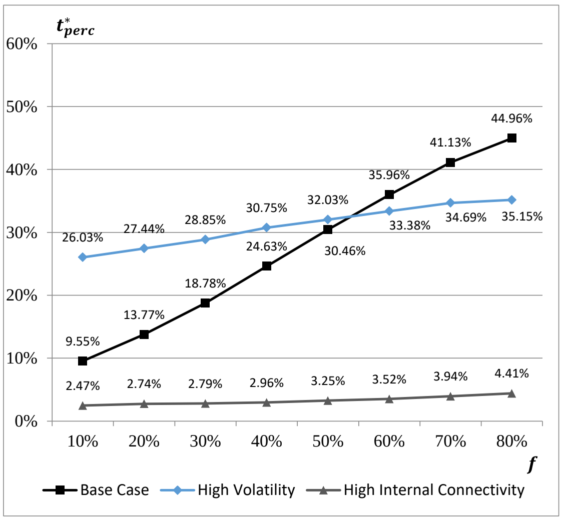

Figure 5b. Varying Failure Rates' Effects on Actual Timing (%)

4.5 Examining the Roles of Incentives

SHD providers seek to accelerate users' switching decisions by using incentives. To test possible incentive schemes, we vary I and i and observe the effects on w_{AM} and t^*_{perc}. Again, we perform the analysis for different volatility scenarios. Finally, to shed more light on the optimal configuration of an incentive scheme, we also vary the delayed, repeated incentive for different sizes of an immediate, one-off incentive.

We start by running our simulation with $I = \{0; 10; 20; 30; 40; 50\}$. Table 4 presents the results, also for the variation in the high-volatility scenario with $\sigma_{E_{ACV2}} = \sigma_{E_{NV2}} = 0.5$. By definition, increasing I reduces the switching costs and positively influences the size of the external connectivity effect. Independently of the uncertainty level, the option value increases in the immediate incentive I (low-volatility case: $w_{AM} = 4.83$ to $w_{AM} = 37.57$; high-volatility case: $w_{AM} = 25.42$ to $w_{AM} = 52.08$). Again, a higher volatility increases the VoW level. Further, increasing the immediate, one-off incentive is very effective in shortening the actual waiting duration if there is little uncertainty: t^*_{perc} decreases by 46.93 percentage points, from 56.72% to 9.79%. In the high-volatility case, t^*_{perc} also is reduced, but only by 11.25 percentage points from 49.73% to 38.48%. Therefore, immediate, one-off incentives are especially useful to accelerate switching decisions in cases with low uncertainty regarding the valuation of SHDs and can also help when there is high uncertainty.

	Low-Volatility Scenario $\sigma_{E_{ACV2}} = \sigma_{E_{NV2}} = 0.05$			High-Volatility Scenario $\sigma_{E_{ACV2}} = \sigma_{E_{NV2}} = 0.5$		
Immediate, One-off Incentive I	Value of Waiting w_{AM}	Actual Timing t^*	Actual Waiting Duration t^*_{perc}	Value of Waiting w_{AM}	Actual Timing t^*	Actual Waiting Duration t^*_{perc}
Simulation Results (Mean Values, 1000 Simulation Runs, Varying I)						
0.00	4.83	207.01	56.72%	25.42	181.50	49.73%
10.00	8.81	168.11	46.06%	29.04	180.36	49.41%
20.00	14.26	126.16	34.56%	33.57	172.00	47.12%
(Base Case) 30.00	21.09	89.91	24.63%	39.10	167.93	46.01%
40.00	28.78	57.58	15.78%	45.08	159.57	43.72%
50.00	37.57	35.74	9.79%	52.08	140.46	38.48%

Table 4. Simulation Results for Varying I and Different Volatilities

Next, we vary i in steps of 0.5 from 0 to 2.0 for low and high volatility. We run these simulations for different values of $I = \{0; 30; 50\}$. Increasing the delayed incentive positively influences the size of the external connectivity effect and raises the costs of deferral by definition. The result is that, for all scenarios, $E(U_2)$ increases from 157.93 to 195.75. The effects of this increase on the VoW and actual timing for both the low-volatility and the high-volatility scenario are shown in Table 5. In all low-volatility scenarios, an increase in i from $i = 0.0$ to $i = 1.5$ results in an increase of the option value, independent of the immediate incentive's value. The higher the delayed incentive is, the lower the actual waiting duration: t^*_{perc} decreases by 61.00 ($I = 0$), 50.19 ($I = 30$), and 20.45 ($I = 50$) percentage points. However, the effects vanish for the incremental change of $i = 1.5$ to $i = 2.0$, indicating that a further increase of delayed incentives is not recommended for suppliers.

	Low-Volatility Scenario $\sigma_{E_{ACV2}} = \sigma_{E_{NV2}} = 0.05$			High-Volatility Scenario $\sigma_{E_{ACV2}} = \sigma_{E_{NV2}} = 0.5$		
Delayed, Repeated Incentive i	Value of Waiting w_{AM}	Actual Timing t^*	Actual Waiting Duration t^*_{perc}	Value of Waiting w_{AM}	Actual Timing t^*	Actual Waiting Duration t^*_{perc}
Simulation Results – Scenario $I = 0$ (Mean Values, 1000 Simulation Runs, Varying i)						
0.00	0.12	343.37	94.07%	18.20	167.31	45.84%
0.50	0.71	322.85	88.45%	19.00	173.43	47.52%
1.00	4.83	207.01	56.72%	25.42	181.50	49.73%
1.50	7.88	118.80	32.55%	30.42	190.77	52.27%
2.00	7.86	120.69	33.07%	30.16	195.69	53.61%
Simulation Results – Scenario $I = 30$ (Mean Values, 1000 Simulation Runs, Varying i)						
0.00	3.41	201.82	55.29%	25.57	169.29	46.38%
0.50	6.83	180.49	49.45%	28.14	173.70	47.59%
(Base Case) 1.00	21.09	89.91	24.63%	39.10	167.93	46.01%
1.50	31.33	18.37	5.03%	46.85	166.28	45.56%
2.00	31.31	18.62	5.10%	46.29	175.06	47.96%
Simulation Results – Scenario $I = 50$ (Mean Values, 1000 Simulation Runs, Varying i)						
0.00	13.44	83.15	22.78%	34.26	156.59	42.90%
0.50	18.80	70.13	19.21%	37.81	157.20	43.07%
1.00	37.57	35.74	9.79%	52.08	140.46	38.48%
1.50	50.95	8.37	2.29%	61.78	130.76	35.82%
2.00	50.93	8.49	2.33%	61.09	147.08	40.30%

Table 5. Simulation Results for Varying i and I for Different Volatilities

These mechanisms differ in the high-volatility scenarios. Even if the change of option values w_{AM} when increasing i is comparable, the effects on t^*_{perc} deviate substantially. For $I = 30$ and $I = 50$, there is neither a clear positive nor a clear negative effect on the actual time to switch. In these scenarios, t^*_{perc} increases in i from 0 to 0.5 ($I = 30$: 46.38% to 47.59%; $I = 50$: 42.90% to 43.07%). Then, t^*_{perc} decreases as i further increases from 0.5 to 1.5 ($I = 30$: 47.59% to 45.56%; $I = 50$: 43.07% to 35.82%) and then increases again if the delayed incentives are further increased to $i = 2$ ($I = 30$: 47.95%; $I = 50$: 40.30%). Therefore, there may be an optimal i to accelerate switching. Interestingly, in the case of $I = 0$, the actual time to wait continuously increases from 49.02% to 55.78%.It is not possible to accelerate users' switching decisions merely by increasing the delayed incentive if volatility is high and there are no immediate incentives. There are optimal values of i from which further increases have an unintended effect for SHD providers. In accordance with the results from Table 4, a higher immediate incentive consistently reduces the actual waiting duration.

We also conducted all analyses with a high level of $DUC_2 = 0.9$ (results available upon request). Although the previously identified effects did not fundamentally change, they were weaker. Accordingly, incentives help when SHN density is high, but they are less effective.

5 Discussion of Results

Our findings identify significant decision mechanisms and relationships between the model's underlying parameters. Important for the interpretation of the results is a careful analysis of the option duration and of users' uncertainty about the expected changes in their valuations of the option underlying. First, we showed that option duration has no significant effect on VoW and only a very small effect on users' actual timing (as a percentage of the option duration). We were able to interpret the results without restrictions despite using only $T = 1$ for all further sensitivity analyses. Second, we tested the consequences of altering volatility and identified that our high-volatility scenarios tended to overestimate option values and waiting durations. We had to consider the findings on option duration and diffusion processes as sort of model relaxations while interpreting the sensitivity analyses' results (Müller et al. 2016).

With these findings in mind, we found two main drivers of the VoW: volatility and the expected utility of the new SHD. On the one hand, users prefer waiting when they face more uncertainty. Interestingly, the product-related uncertainties regarding the internal connectivity in the SHN have a stronger impact than the market-related uncertainties of the external network. On the other hand, high expected values for a new SHD's utility lead to higher option values; it promises the opportunity to switch to a new device that provides higher utility gains. This is in line with research on firms' IT investments stating that higher valuations of an option underlying accelerate investment decisions (Ji 2010; Li 2009).

Next, we identified clear roles of internal and external connectivity effects and their interaction. Since the possibility of internal and external connections is inherent to SHDs, this analysis is highly relevant. Its focus on private users complements existing research on how network effects influence option values from a provider perspective (Kauffman and Kumar 2008). Generally, more internal or external connections increase an option's value and reduce the actual waiting duration because a higher connectivity and a greater external network size both raise the new SHD's expected valuation and, accordingly, the costs of deferral. Product-related and market-related uncertainties weaken the influence of both CV as well as NV. Interestingly, sensitivity analysis showed that high internal connectivity leads to early switching, independent of the external connectivity effects. Therefore, compatibility with many of a user's other devices fosters their willingness to use an SHD. The possibility to integrate SHDs into dense SHNs can explain why certain devices exist that diffuse rapidly after their introduction in the market. In recent years, this can be observed for smartphones, which often serve as a control unit for SHDs, and for which several previously unknown manufacturers have profited from compatibility within the Android ecosystem and reached large market success within a short time.

Finally, our results provide insights for configuring incentive schemes for SHD providers. Immediate, one-off incentives were effective in every scenario, and a higher volatility only weakened the effects. These incentives accelerate switching decisions since they increase an option's value and therefore encourage users to switch earlier. Despite this, the provision of delayed incentives was useful only up to a certain threshold. When further increased, they had no additional positive effect on an option's value and did not further reduce the actual switching timing. If volatility was high, we could even identify an effect contrary to the application of immediate incentives: later switching became more likely when the delayed incentives exceeded a critical level. This is in line with findings from marketing research: in markets where users show strong deferral behavior (which corresponds to our high-volatility scenario), immediate incentives are more effective than delayed ones (Zhang et al. 2000). An explanation could be that immediate incentives not only have a direct monetary effect, but also reduce activities to search for information as subsequent information is of no consequence. Delayed incentives do not have this effect on requiring information because they are offered later. Further, they also show some uncertainty concerning realization. This could be a problem, especially in high-volatility scenarios, since early and fixed measures to reduce uncertainty are necessary. Therefore, an optimal SHD provider incentive scheme should primarily use high immediate incentives and can be extended with a limited amount of delayed incentives. Both incentive types are effective, but delayed incentives are only effective up to a certain level, since they can cause counter-intuitive effects in high-volatility scenarios after exceeding a certain amount.

6 Conclusion

6.1 Theoretical Contributions

The possibility to wait has its own value because uncertainties can be reduced. To our best knowledge, no approach has employed this VoW concept as an explanation for deferred decisions in private users' technology management. We provided an option model that allows the analysis of the role of deferring in switching decisions from a private user perspective. The focus on SHNs as an innovative environment that is characterized by connectivity-driven uncertainty, and the application of a context-specific SHD valuation, further differentiate our approach. To be able to investigate the decision scenario of SHD switching, several enhancements that collectively allow the calculation of actual switching timing were required as well as examination of the influences of internal and external connectivity and incentives:

- the combination of internal connectivity and external connectivity to define the option underlying
- the combination of deferral and switching costs in one model and its extension to account for provider incentives that are related to both cost types
- the representation of uncertainty in the development of expected utilities using a Geometric Brownian Motion for product-related uncertainties and a jump diffusion process for market-related uncertainties
- LSM simulation for the different diffusion curves and the combined option to defer switching (Kou 2002; Longstaff and Schwartz 2001).

Even if the specifications are set by a decision scenario, the general procedure to adapt models to critical decision semantics can also be used for other ROAs in the private user context. Our model explains why uncertainty reduction and timing aspects are relevant factors in switching decisions for connected devices in SHNs. We have shown that determining the VoW is critical to derive a comprehensive valuation of an SHD, highlighting that this utility should not be ignored in theoretical explanations of users' switching behaviors, at least if users' decisions are not restricted by fixed dates. We urge researchers to incorporate these ideas so as to provide a more realistic perspective of how users decide between different technology generations.

This study also contributed to IS switching theory by deriving specific intertemporal effect mechanisms of users' behaviors and decision criteria based on our sensitivity analysis. It highlights the dynamic aspects in switching decisions by simulating expectations during the option and the usage duration. We extend previous research on deferral in network industries (Kretschmer 2008) by demonstrating that compatibility in form of connectivity is a main driver for earlier switching decisions and accelerating market diffusion.

6.2 Practical Implications

While our focus is on firm-consumer interaction, our findings are also relevant for other institutions, such as governments, which may wish to nudge their citizens/customers to use new technologies (e.g. smart meters) on a broad scale. There are two major aspects concerning the practical relevance of our findings: First, understanding the roles of the VoW and its determinants in switching decisions forms the basis to build profound knowledge about users' switching behaviors. Second, understanding incentives' impacts on actual timing in different scenarios facilitates the configuration of incentive schemes. Both aspects are crucial when SHD providers need to quickly accelerate the diffusion of their devices.

Our calculated actual times to switch indicate on average when SHD providers can expect their customers to take a switching decision. This helps to identify the relevant users for providers' incentive schemes. In many switching decisions, uncertainty is a critical factor to consider since it prevents users from early switching. Our study has shown that the influences of product-related uncertainties are greater than that of market-related uncertainties. Therefore, SHD providers' information campaigns should focus on the utility of the additional application fields if the device is integrated into the SHN rather than highlighting the already established market diffusion. An example is Apple. The company frequently enters new markets (e.g. when launching the first iPhone, iPad) and provides their customers with continuous ease of use and compatibility of the devices within the Apple ecosystem.

Since users value the possibility to wait, SHD providers should offer incentives to counteract this motivation for deferral behavior. We found that immediate, one-off incentives are the most effective since they not only provide additional utility to users, but also reduce their motivation to search for further (potentially negative) information. These incentives are often used by software vendors, such as Microsoft, who offered the Windows 10 at a considerably lower price, or even for free, to users who decided to switch from older Windows versions before a specific date. Providers need to be more careful with delayed incentives; these are also effective and can support immediate incentives, but only up to a certain threshold. Exceeding this threshold can also cause undesired effects on switching timing, especially in cases of high uncertainty. SHD providers should primarily use high immediate incentives. Based on their sales and pricing strategy, they can extend these with limited delayed incentives if needed. While it may appear logical that immediate incentives can have a stronger impact on switching decisions than delayed incentives, we still observe manifold related examples in practice (such as telecommunication contracts) for which delayed incentives still play a large role. We therefore believe that these insights are particularly helpful in the current stage where SHD diffusion is still moderate.

It is also important for providers to know that, in scenarios with high internal network density, the VoW and the actual waiting duration do barely depend on external connectivity effects. This means that even without a large installed base to exploit external connectivity effects, SHD providers can still cater for users with dense SHNs by supplying highly compatible SHDs. This is important to facilitate new market entries.

We acknowledge that most users may not have the tools to conduct our calculations. However, even if humans are often not rational, models assuming rational decision makers are widely used to successfully explain various phenomena. Moreover, departing from the rationality assumption opens up a plethora of possibilities that endangers modelling assumptions to become arbitrary. We think it is a viable way to start with the rationality assumption, although this is clearly not perfect. From a more practical point of view, institutions such as consumer representative organizations might have the required knowledge and tools for the calculations. They could use them as a basis for product tests and to support individual consumers in their purchase decisions. Our model could also serve as a basis for an implementation in recommender systems that could be offered by technology suppliers or independent websites that seek to assist consumers in their purchasing decisions.

6.3 Limitations and Opportunities for Future Research

After demonstrating that our model is suitable to analyze users' SHD switching decisions and inform providers on their incentive strategies, our work also provides a solid basis for future research, especially considering the enhancement of numerical solutions and the application of empirical data.

As noted, using the Geometric Brownian Motion and the jump diffusion process to predict the development of users' expected valuations does not fully capture the decision semantics; the decreasing uncertainty while waiting and gaining information cannot be implemented in our approach. We solved this problem by performing sensitivity analysis to examine the impact of reduced volatility on our results. However, future studies can work on the integration of other stochastic differential equations. Such extensions could provide enhanced solutions that are more exact in terms of fit for other scenarios.

We used a combination of suitable values and randomly generated data to find numerical solutions when running our simulations, in line with our goal to present a framework for switching behavior and to use it exemplarily. Our numerical results have to be interpreted with this background in mind: They show the potential outcome within a range of reasonable parameter values. In this sense, we identified the underlying effects and their directions, and provided well-interpretable results. However, we cannot conjecture that these effects hold for every SHD/SHN product. The exact model parameters, and maybe even some necessary modifications to the model itself, clearly depend on product, company and strategy. Obviously, future research may also extend our data generation process, for instance, by performing empirical research in the form of conjoint analyses for actual products on the market, to allow for a specification of relative importance and utilities of device features. Thereby, a similar model could be applied to field data or quasi-field data, as has been done in other studies (Harmantzis and Tanguturi 2007; Henseler and Roemer 2013). Another opportunity would be to contrast our model with other explicit switching models (such as the push-pull-mooring framework), which might also profit from integrating the value-of-waiting concepts into their underlying basis.

While explaining users' switching behaviors for connected devices is currently already of high interest, its importance is likely to increase. Future devices and technologies will be increasingly connected, opening the door for more complex interactions and dependencies between devices, not only in Smart Home or other private usage contexts, but also for other applications in professional contexts, such as digitized production processes or traffic coordination. Our findings can serve to guide research into decision behaviors and can inform investment decisions concerning emerging technologies.

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Appendix

Parameter	Value	Definition	Explanation
Stand-alone Utility A			
A_1	60	Stand-alone utility of an SHD	Value represents stand-alone utility of SHD1 as a basis to calculate the stand-alone utility of SHD2
s_2	5	Deviation factor	Determines the extent to which SHD2 outperforms SHD1 concerning the stand-alone utility
Connectivity-related Utility CV			
DUC_2	0.5	Degree of utilized connectivity (SHD2)	Value represents a certain share of possible connections between SHDs that is already realized.
DUC_1	0.3	Degree of utilized connectivity (SHD1)	Value represents a certain share of possible connections between SHDs that is already realized. Lower values for SHD1 indicate that it is less integrated than SHD2
$H_{2,ex}$	30	Expected internal network size for SHD2 (within 5 years)	Expected number of SHDs if user decides for SHD2
$H_{1,ex}$	18	Expected internal network size for SHD1 (within 5 years)	Expected number of SHDs if user decides for SHD1. Smaller since SHD2 is better integrated.
$H_{2/1}(ddt = 0)$	10	Internal network size at option start	User has already some SHDs in the internal network to connect with SHD1 or SHD2
α	0.03	Growth coefficient for internal network	Denotes how strongly the integration of existing SHDs influences the integration of new SHDs into the internal network
Network-related Utility NV			
$b_{2/1}$	1.5	External network valuation factor	Marginal utility of a new user in the external network
f	0.4	Market failure rate of SHD2	Denotes the probability for which SHD2 is likely to miss the necessary installed base for market success
β	0.02	Growth coefficient for external network	Denotes how strongly the previous integration of users influences the future integration of other users
$N_{2/1}(ddt = 0)$	150	External network size at option start	Denotes the number of other users at the option start date
$N_{2,ex}(Pr = 1 - F)$	450	Expected external network size with SHD2 if SHD2 is successful	If SHD2 is successful, its external network increases strongly
$N_{2,ex}(Pr = F)$	50	Expected external network size with SHD2 if SHD2 is not successful	If SHD2 is not successful, its external network decreases strongly
$N_{1,ex}(Pr = 1 - F)$	125	Expected external network size with SHD1 if SHD2 is successful	If SHD2 is successful, SHD1's external network decreases
$N_{1,ex}(Pr = F)$	200	Expected external network size with SHD1 if SHD2 is not successful	If SHD2 is not successful, SHD1's external network increases
Values for Variables in Option Calculation			
γ	0.05	Deferral cost rate	Analog to dividend yields because of switching too late
r	0.03	Exercising cost rate	Analog to dividend yields because of switching too early
i	1.00	Delayed incentives rate on deferral costs	Part of multiplicative factor $(1 + i)$
I	30	One-off incentives	Extent offered to users at the time of switching
K	50	One-off switching costs (lump sum)	Accruing costs to users at the time of switching
$\sigma_{E_{ACV2}}$	0.05	Standard deviation of changes in the development process of expected utilities	Volatility in Geometric Brownian Motion for SHD2
$\sigma_{E_{ACV1}}$	0.01	Standard deviation of changes in the development process of expected utilities	Volatility in Geometric Brownian Motion for SHD1
$\sigma_{E_{NV2}}$	0.05	Standard deviation of changes in the development process of expected utilities	Volatility in Jump Diffusion Process for SHD2
$\sigma_{E_{NV1}}$	0.01	Standard deviation of changes in the development process of expected utilities	Volatility in Jump Diffusion Process for SHD1
λ	0.05	Mean number of jumps per unit time	Probability of jumps in Jump Diffusion Process

Table A1. Values for Data Generation and the Calculation of Solutions (Base Case)