Simulating the *Value of Waiting* in Users' Switching Behavior - a Real Option Approach Concerning Smart Home Systems

Complete Research

Abstract

Product-related uncertainties often let users hesitate concerning switching to new systems. This possibility to defer decisions allows them to benefit from more information and, thereby, reduced uncertainties. Waiting before switching is especially relevant when system interdependencies make isolated switching decisions more difficult for private users, for instance in the case of Smart Home Systems (SHSs). This value of waiting (VoW) perspective on individual inertia emphasizes decision dynamics in such switching situations, but is far from being fully understood. Thus, we explore users' decision mechanisms for optimal switching timing based on VoW calculations and we examine the influence of system-interdependent features such as connectivity on VoW and optimal time to switch.

To this end, we postulate a real option model that combines elements of switching and deferral concepts and that represents VoW in terms of option premiums. Based on comprehensive underlying valuations, we use simulation methods to find numerical solutions for VoW and optimal time to switch. Overall, the study's findings show why uncertainty reduction and timing aspects are relevant factors in users' decision mechanisms. Furthermore, we learn that the effect of system interdependencies on individual inertia depends on the point in time at which corresponding utility gains can be realized most effectively.

Keywords: Real Option Approach, Value of Waiting, Inertia, Switching Behavior, Smart Home Systems, Home Networks, Private User.

1 Introduction

Private users are often prevented from replacing existing systems by switching to newly emerging ones on short notice. Thus, they tend to prefer a current course of action in their post-adoption behavior when facing critical uncertainties regarding emerging systems, even if new alternatives promise better features. This so-called inertia reflects a misperception towards the status quo and causes a deferral in the decision-making process (Polites and Karahanna, 2012). It also poses a critical challenge if sticking to the incumbent system is inefficient (Rumelt, 1995). Despite this, users can also enjoy a real positive utility effect by deferring an incumbent system's replacement. The idea behind this *value of waiting* (VoW) is that switching to a new system is accompanied by much uncertainty regarding the new system's future utility (Kim and Kankanhalli, 2009). By waiting to switch, uncertainty can be decreased, because users gain access to more information and can learn about the new functionalities, and about the likelihood of the new system's market success (Dong and Saha, 1998). Additional utility is thus derived, because the possibility to defer switching is valued positively owing to uncertainty reduction. It causes a trade-off between reducing product-related uncertainties and realizing early utility gains from immediate system switching. Adopting the new system too early carries sunk costs when product-related uncertainties are negatively confirmed. Adopting too late risks the loss of significant benefits. The result is that users can maximize their utility by choosing the optimal moment to adopt a new system (Kauffman and Li, 2005).

The decision problem becomes even more complex since new systems increasingly show significant interdependencies to related systems in certain usage situations. Thus, isolated adoption decisions become less frequent, and users must consider effects on other systems and on joint usage when switching. The result is an even higher product-related uncertainty that will further affect timing in switching behavior. These system interdependencies often are the result of connectivity features. Besides to linking with other users in external networks, connectivity also allows systems to connect to each other. One example are Smart Home Systems (SHSs) that can be used to build private home networks (Venkatesh, 2008). Here, connectivity means that users can link different devices and smart products from various product categories – for instance, a smartphone and a heater – that had not been linked and used jointly before (Herbrechter et al., 2011). Especially for SHSs, users face significant product-related uncertainties concerning system performance and its future value, especially in terms of technical compatibility or systems' task-related fit into home networks (Dimoka et al., 2012).

We analyze VoW and timing mechanisms in the context of SHSs. Thus, we interpret the concrete switching decision as users' real option to adopt or not to adopt a new SHS and to substitute or not to substitute the incumbent system. Users also have the possibility to defer the decision until a utility-maximizing point in time. Such real option approaches (ROAs) are applied broadly in IS research into corporate IT investments and adoption (Ji, 2010; Kauffman and Li, 2005; Li, 2009; Schwartz and Zozaya-Gorostiza, 2003). In the organizational context, previous work has also recognized that utility-maximizing timing depends on other decisions about related systems that are used jointly to accomplish certain tasks (Hoppe, 2002). However, at the individual level the VoW perspective on users' inertia in system switching behavior is far from being fully understood. Especially when usage possibilities can only jointly be exploited, there is a research gap regarding private users' optimal switching timing and valuation dynamics concerning interdependent systems, such as SHSs. Thus, we have two research goals. First, we need to know: how can we explore decision mechanisms for individuals' system switching based on concrete VoW calculations? Second, we pose the question: how does connectivity influence utility gains and timing decisions?

To answer these questions, we construct a unified formal model that allows us to concretize and to price the VoW in end-users' switching decisions. We also consider the decision's dynamic aspects and formalize users' opportunities to defer their switching behavior in the option model. Thus, the model combines elements of general switching and deferral concepts (Kauffman and Li, 2005; Kumar, 1996; Loraas and Wolfe, 2006). We concretize the model via the option underlying to apply it to connected SHSs in home networks and calculate option values and optimal points in time for switching by means of least square Monte Carlo (LSM) simulation methods. The solutions promise further insights into decision-making and effect mechanisms that go beyond typical empirical IS post-adoption models, such as the expectation-confirmation model or the push-pull-mooring framework (Bhattacherjee, 2001; Ye and Potter, 2011).

Therefore, we integrate a dynamic perspective into system switching to consider uncertainty in intertemporal decisions. This is often ignored because current switching behavior models are mostly static (Henseler and Roemer, 2013). Yet we are able to represent users' decision flexibility, timing strategies, and decision dynamics in home network management by implementing the option value as a component of system valuation. To concretize, we provide a formal model to explore optimal switching timing for the private user context. Furthermore, we demonstrate how system-related interdependencies can affect users' decisions by analyzing effects of connectivity in SHS switching. In the model development process, we also show how to methodically adapt the LSM approach to fit combined deferral/switching options. Besides theoretical contributions, our model potentially offers insights to SHS suppliers regarding the proper timing and extent of incentives to foster switching behavior and a faster market diffusion.

2 Theoretical Background

2.1 Individual inertia and value of waiting concept

When users defer their switching decisions, they do not only get the possibility to reduce uncertainty. They are also motivated to perform a type of inaction that makes them stick to the status quo, here using the incumbent system (Khan and Stinchcombe, 2015). In general terms, this inertial behavior becomes an important factor if users are to some extent familiar with a usage situation, which involves the tendency to continually repeat the same action or inaction (Bawa, 1990). Such behavioral continuance exists, because people tend to justify recent decisions by iterating them (Gupta et al., 2007). Such individual-level inertia is determined by a persistence to continue utilizing incumbent systems even if there are better alternatives or other incentives to change (Polites and Karahanna, 2012). When behavior is biased in this way, cognitive misperceptions and psychological commitments are valuable explanations for users staying with an incumbent system (Samuelson and Zeckhauser, 1988). Sticking to the status quo has the consequence that perceptions of switching costs and lock-in effects around a system are increased, which prevent users from switching to other suppliers or new technological alternatives (Chen and Hitt, 2002). Inertia as form of decision deferral can impede switching and should thus be considered as a psychological factor in post-adoption decision phases (Polites and Karahanna, 2012).

Despite this, waiting and deferring a decision can also have a positive utility effect for users. The VoW concept embraces this other view on consequences from inertial behavior. Accordingly, waiting can be used deliberately to improve one's switching decision. This suggests that the possibility to defer taking a decision adds to user value in situations with significant product and market uncertainties (Henseler and Roemer, 2013; Loraas and Wolfe, 2006). Waiting in this sense increases a system's valuation, because it decreases uncertainties about its functioning and its likelihood of success, as more and better information becomes available over time (Dong and Saha, 1998; Hoppe, 2002). For instance, users can get information about market shares, which is important especially for network effect goods, or they can test the various products and learn about their functionalities and their connectivity features. In this way, one can decrease the risks of substituting a system too early or of including a system that is not compatible to other related systems. Thus, by adding the waiting perspective, we get some kind of utility-based inertia that occurs when usage continuance is motivated by uncertainty reduction. This utility should be assessed by finding a representation of VoW in the form of real option premiums.

2.2 Real option approach and system adoption

Users have the choice of when they want to switch and if they want to switch at all. This means that they have the opportunity to switch to new systems in future, but there is no de facto necessity, at least as long as the incumbent systems still work. Thus, users' switching and usage decisions embed different forms of real options (Saya et al., 2010). Generally, a real option is defined by the right to take a certain future (in)action without any obligation to take it (Copeland and Antikarov, 2001). In financial terms, switching options represent the combination of a put option and a call option. A put option refers to quitting the incumbent system and a call option to using the new one instead (Kulatilaka and Trigeorgis, 1994). Furthermore, the option to defer implies the possibility to learn about a system and provides the opportunity to delay a decision until enough information has been collected (Saya et al., 2010). To ensure applicability of ROAs, it is important that (at least) partial investment irreversibility and uncertain economic benefits hold true, otherwise users could reverse an investment without monetary loss and could take definite actions about their future actions (Adner and Levinthal, 2004).

To determine a specific value for an option, Black and Scholes (1973) – and especially Margrabe (1978) for switching options – have derived the fundamental equations to identify values of European-type options that can be solved analytically. Regarding real options, these models are not wholly appropriate, since their basic assumptions – such as a de facto perfect market or a fixed maturity time – can hardly be fulfilled. The problem is that the models consider mostly market-related risks, but more or less ignore project-specific ones, which we would interpret as equivalent to product-related uncertainties of SHSs in our private user context (Diepold et al., 2009). Thus, for assumption relaxation in real option pricing, we must adapt the financial models concerning the underlying's valuation and stochastic simulation paths (Ullrich, 2013).

In IS research, ROAs are mostly applied to get a valuation of firms' IT investments when intertemporal dependencies and future economic benefits must be taken into account (Dos Santos, 1991). To assess IT investment values, it is recommended that one can add the project's action flexibility value to their net present value (Trigeorgis, 1996). Thus, the integration of action flexibility in terms of a *wait and see* strategy allows one to account for deferral. The option values then approximate the investments' fair values, because uncertainties can be decreased over time (Benaroch, 2002). This is exactly the link between the inertia concept and real option models we elaborate on and that we use to analyze the right timing for switching decisions. Generally, the relationship between users' perceptions of their deferral options and IT adoption is also confirmed by a number of empirical studies of the influence on behavioral intentions (Goswami et al., 2008; Saya et al., 2010). Previous work that applied ROAs to technology adoption mainly focused on the company perspective. Many studies are emphasising option value calculations as means for managers' risk management regarding IT investment decisions (Dos Santos, 1991; Harmantzis and Tanguturi, 2007; Heinrich et al., 2011). These studies describe how investments can be justified by using ROA-based argumentation. Other research projects have used option models to derive optimal timing strategies for technology adoption (Ullrich, 2013). Authors can thus underline the strategic relevance of the right timing for actions and decisions (Sollars and Tuluca, 2012). The studies' findings show how optimal timing in IT investment decisions can be modelled for competing IT projects (Kauffman and Li, 2005), or how organizational knowledge and learning capabilities affect the right timing in IT adoptions (Ji, 2010; Li, 2009). We use both – value calculations and optimal timing analysis – for this research project.

3 Real Option Model Development

We develop a real option model that represents end-users' VoW derived from the possibility to replace an incumbent system with a new alternative, and from the possibility to defer this switching decision to a future point in time. We apply it to a certain decision situation in which users have the possibility to switch from one SHS to a new one with even better connectivity features to integrate it into the already existing individual home network.

We take two different option model strands and combine both their relevant elements in our model approach. First, we build on real option models that concern individuals' private switching behavior (Haenlein et al., 2006; Henseler and Roemer, 2013). To concretize, we examine how these models are adapted to fit the individual decision context. Second, we examine ROAs that consider the value to defer new systems' adoption, yet in corporate contexts (Benaroch and Kauffman, 1999; Harmantzis and Tanguturi, 2007), and seek to identify important elements for analyzing optimal timing. Then, to develop the new model, we combine both strands and make necessary adaptations concerning SHS in home networks via the option underlying. The procedure is summarised in Figure 1.

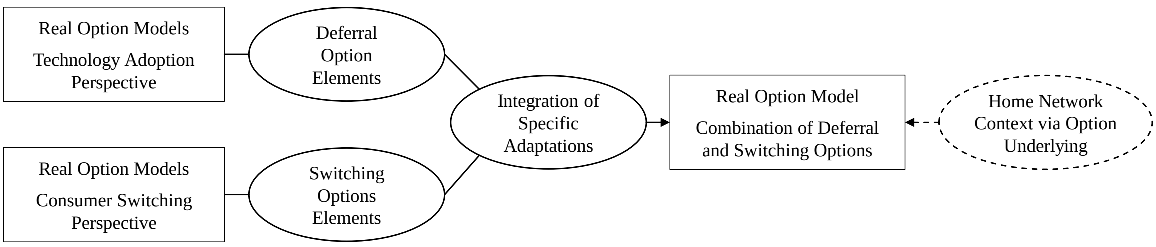

Figure 1. Model development procedure.

3.1 Real option model analysis and adaptation

In our context, the option to switch is determined by the possibility to replace an incumbent SHS with the new alternative. Thus, the decision to leave the old system represents a quasi-put option and the decision to adopt the new system represents a quasi-call option. Margrabe's (1978) model is generally applied to solve the calculations of such option values. The model involves the following logic: a European option to substitute one risky asset for another yields the difference between asset 2's price and asset 1's price if exercised at a certain point in time (time to expiration T), or nothing if not exercised (Margrabe, 1978). With asset prices X_2 and X_1, each asset's return rate follows a geometric Brownian motion given by

$$dX_j = X_j \, [(\mu_{X_j} - \delta_{X_j})dt + \sigma_{X_j} dz_j] \;\; (j = 1, 2), \tag{1}$$

where μ_{X_j} and σ_{X_j} denote expected return rates, and standard deviations, dz_{X_j} denotes the increment of a standard Wiener process at time t with $dz_j \sim N(0, dt)$, and δ_{X_j} denotes dividend yields (Carr, 1995). This stochastic differential equation follows an upward trend with positive and negative variations.

The option premium w is determined by the actual switching value as deterministic element and the value to defer as stochastic element. The former component equals the difference of X_2 and X_1 and represents the real option's intrinsic value. The latter component reflects the option's time value originating from users' possibility to defer switching (Brenner and Subrahmanyam, 1994; Henseler and Roemer, 2013; McDonald and Siegel, 1986). Thus, the initial equation for the option value is given by

$$w(X_2, X_1, T) = \max(0, X_2 - X_1). \qquad (2)$$

McDonald and Siegel (1985) find that this switching option type's value is then formulated by

$$w(X_2, X_1, T) = X_2 e^{-\delta_{X_2} T} N(d_1) - X_1 e^{-\delta_{X_1} T} N(d_2), \qquad \text{with} \qquad (3)$$

$d_1 = \frac{\ln(X_2/X_1) + (\delta_{X_1} - \delta_{X_2} + 0{,}5\sigma^2)T}{\sigma\sqrt{T}}$, and $d_2 = d_1 - \sigma\sqrt{T}$.

Here, σ^2 denotes the variance of $(X_2/X_1)^{-1} * d(X_2/X_1)$, and $N(*)$ represents the standard univariate normal distribution function.

Two major adaptations are needed to transfer the model to a user context. First, the right option underlying must be found. Because a real option to switch is actually not about substituting financial assets, we need a concept that reflects the investment's value for users. To assess a underlying, other studies refer to the net customer value (NCV) as a proper instrument. Since, for instance, future prices are fairly unstable, uncertainty about the development of users' benefits and costs are integrated into the NCV concept (Haenlein et al., 2006; Henseler and Roemer, 2013). Owing to this uncertainty, it is necessary to extend a present value based instrument that measures the underlying, such as the NCV, with the value of action flexibility (Trigeorgis, 1996). This means that a monetary-like option premium is added. Thus, a comprehensive investment valuation can be derived as the sum of the underlying's present value and its option premium. The second major change concerns the occurrence of switching costs, such as learning, setup, or economic risk costs when users do decide to switch. Users lose not only the incumbent investment's value, but also pay the purchasing price for the new investment and must bear related switching costs, This means that the option's exercise price is raised by the switching costs K in terms of a lump sum (Burnham et al., 2003; Henseler and Roemer, 2013). We derive $X_1 + K$ as the exercise price. We see that defining an appropriate underlying that is able to reflect the priority of the decision alternatives in value terms is indispensable. We also have to consider the role of switching costs for users.

In the case of system adoption, real options, furthermore, are mostly modelled as options to defer. This means that the decision to adopt or switch can be delayed for a flexible period until the option premium is maximized (Benaroch and Kauffman, 1999; Harmantzis and Tanguturi, 2007). To apply ROAs, the actual adoption must be characterized by uncertainty and flexibility (Harmantzis and Tanguturi, 2007). System adoption requires relatively high, significant irreversible, upfront expenses. However, these IT investments are fairly risky with respect to market success, owing to network externalities and standardization or compatibility effects (Farrell and Saloner, 1985; Katz and Shapiro, 1994). Action flexibility can be assumed in these situations, since there is no obligation to adopt new alternatives (Kauffman and Li, 2005). In financial terms, deferral options are equivalent to American call options. They give an owner the possibility to adopt at any future date before or on the expiration date. Deferral should be more valuable than a now-or-never decision, because it provides the option owner with the opportunity to gather more information. However, users cannot profit from possible benefits of a new system while waiting (Benaroch and Kauffman, 1999). This trade-off explains that there is an optimal moment for them to adopt or to switch.

Usually, deferral option models allow for the integration of annual deferral costs, since the option owner foregoes probable yields by not using a new system immediately. In contrast, adopting too early risks the loss of a risk-free interest rate (Harmantzis and Tanguturi, 2007). We also have to consider this trade-off in our model, with the difference that the dividend rate on the incumbent system is not perfectly risk-free, but provides users with a fairly constant and well assessable utility. Furthermore, there are no analytical closed-form solutions for deferral options owing to flexible option exercising. Therefore, it is necessary to use approximation processes or simulation methods (Benaroch and Kauffman, 1999; Harmantzis and

Tanguturi, 2007). We also see that there is no fixed time to exercise our type of combined option. An investment in a new SHS is possible at any time within the expiration period. Thus, we also need simulation-based estimations to calculate option values and optimal timing.

3.2 Real option applicability and underlying definition

To concretize the model for SHS in home networks, we must define an appropriate option underlying for investment valuation. Using a ROA is adequate for such system types, since market and product-related uncertainties are major concerns. A system's market success and internal home network compatibility strongly depend on network effects and standard diffusion, which are both difficult to predict (Dimoka et al., 2012; Farrell and Saloner, 1985; Katz and Shapiro, 1994). We can also affirm decision flexibility and relatively high investment costs, at least for private users, so the determining factors of our decision situation allow us to apply ROAs.

To formalize the underlying, it is important to understand how we can measure the value an SHS has for users. We therefore take a utility function approach, where the system's utility reflects the private users' willingness-to-pay. SHSs are characterized by the combination of digital and physical components which allow for the integration of information system technologies into household products. This also implies the utilization of connectivity technologies as the basis for building home networks (Venkatesh, 2008). For instance, in the case of smartphones, there can be exogenous connections to other users and internal ones to other SHSs in the private network. The latter connectivity type leads to a user-centered utility in SHS valuation (Berger et al., 2016). Thus, the total utility (U_j) of system j comprises three components: first, a stand-alone benefit from basic functionalities (A_j), for instance a smartphone's alarm application; second, a connectivity-related benefit (CB_j) originating in connections between SHSs; third, a network-related benefit (NB_j) originating in connections to other users (Berger et al., 2016; Matutes and Regibeau, 1996). We therefore derive

$$U_j = A_j + NB(b_j, N_j) + CB(c_j, DUC_j, H), \tag{4}$$

where $A_j, b_j, c_j > 0 \wedge N_j, H \in \mathbb{N} \wedge DUC_j \in [0, 1]$. Thereby, N_j denotes the exogenous network size, and b_j denotes the external network valuation factor (Matutes and Regibeau, 1996). Furthermore, H denotes the number of SHSs in a home network, c_j denotes the connectivity valuation factor, and DUC_j represents the degree of internal network density (Berger et al., 2016). Equation 4 shows the different aspects users use in assessing their SHS valuation. However, users cannot be sure how the valuation develops in later periods. Thus, we need to use the expected utilities to represent the underlying's value. Users also face uncertainties concerning network effects, which influence NB_j, and concerning standard diffusion and compatibility, which influence CB_j. Owing to these unpredictable risks about the future utility, it is possible to extend the expected utility by the value of action flexibility w – the option premium (Trigeorgis, 1996). Finally, we take the discounted future utilities into account, to integrate a net present value perspective (Henseler and Roemer, 2013). Thus, users evaluate their investments in SHSs by considering the present value of anticipated net utility gains from a system's future usage possibilities and by considering how much the option to defer is worth to them. We derive the total SHS valuation ($EU_{j,Total}$), integrating the expected net present utilities as perceived by users:

$$EU_{j,Total} = E(U_j) + w = E\left(A_j\right) + E\left(NB_j\right) + E(CB_j) + w. \tag{5}$$

We assume that users evaluate both the incumbent system and the new alternative accordingly. Here, for $j = \{1, 2\}$ $E(U_2)$ and $E(U_1)$ are used to determine the actual switching value.

3.3 New model specification

We specify our real option model to derive the VoW in home network switching situations by building on the context-specific option underlying from the previous chapter. In general, our model is based on switching option models, similar to equation 3. However, some further adaptations are needed. For the development of returns on users' expected net present utility $E(U_j)$ in future periods, we assume a stochastic process that moves up and down in continuous time with an upward trend. Owing to habituation, users better know how to handle a system and increasingly exploit its utility in the long term, especially when they learn how to use an SHS with others in the home network. Since it is a typical type of stochastic differential equation to model uncertainty in option valuation (Carr, 1995), we also use a geometric Brownian motion with drift to indicate these characteristics:

$$dE(U_j) = E(U_j)\,[(\mu_{E(U_j)} - \delta_{X_j})dt + \sigma_{E(U_j)}dz_j] \qquad (j = 1, 2), \tag{6}$$

with $\mu_{E(U_j)}$ as the expected utility's expected growth rate and with the standard deviation $\sigma_{E(U_j)}$ as its volatility. Again, δ_{X_j} represents dividend yields and dz_j denotes the increment of a standard Wiener process with $dz_j \sim N(0, dt)$ (Carr, 1995; Margrabe, 1978).

We model a distinct option type that is viable for users' technology switching in general, but is concretized for the study context by integrating our determined underlying. Users have the option to switch, since it is actually possible to change and replace an SHS in the home network with a newer one. Users also have the possibility to defer this move to a new SHS generation until they have enough information so as to feel safe. However, they do not have to switch at all and can abandon the option. We further assume that returning to the incumbent system after switching is excluded, since we are focusing on the combination of deferral and switching and its analysis. Furthermore, such compound switching options would represent a more complex extension of our model that could be analyzed in follow-up research projects. The decision process is illustrated in Figure 2.

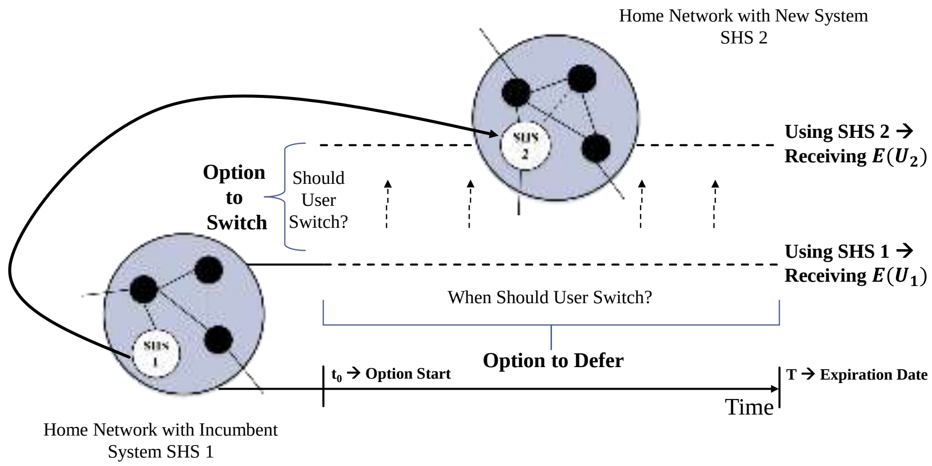

Figure 2. Combined deferral and switching option for SHSs.

In our model, where users' decision situation is about the possibility to switch from SHS 1 to SHS 2, SHS 2's quasi-asset price is reflected by its present value in terms of users' expected net present utility $E(U_2)$. The option exercise price is reflected by SHS 1's quasi-asset price $E(U_1)$, which would be lost, plus switching costs in form of a lump sum (K). For instance, users must invest extra time in learning to use the new SHS or buy new complementary products for the home network (Burnham et al., 2003; Henseler and Roemer, 2013). We must also integrate a deferral cost rate γ ($\gamma = \delta_{X_2}$) on SHS 2's utility and a dividend yield in the form of an exercise cost rate r ($r = \delta_{X_1}$) on SHS 1's utility. This reflects the trade-off between reducing information gains owing to switching too late and probable losses in terms of lost benefits from using the new system too early (Harmantzis and Tanguturi, 2007). By regarding these modifications, we adapt the switching model in equation 3 for the valuation of our combined option (w). We derive

$$w(E(U_2)\,,E(U_1)\,,K,T) = E(U_2)\,e^{-\gamma T}N(d_1) - (E(U_1)\;+K)e^{-rT}N(d_2), \qquad \text{with} \qquad (7)$$

$d_1 = \frac{\ln(E(U_2)\,/(E(U_1)+K))+(0{,}5\sigma^2-\,\gamma\,+\,r)T}{\sigma\sqrt{T}}$, and $d_2 = \; d_1 - \sigma\sqrt{T}$.

Again, T denotes the time to expiration and σ the standard deviation of the expected return rate on the option underlying. We assume $\gamma > r$ to integrate the fact that using the incumbent system implies less uncertainty than using the new one. Yet, we need an interpretation for T in our context. Users can exercise their option at any point in time between the option start and expiration date. This would imply that, after expiration, switching is no longer possible. Since this restriction does not seem logical, we interpret T as the time to the release of the next technology generation. Thus, it would make more sense to switch to the newest SHS and to skip the option. From equation 7, we derive the European-type option value. However, to allow for flexible option exercising, and thus to formalize the deferral option, we must calculate the American-type value. To make this work, we carry out analytical steps by applying a least square Monte Carlo (LSM) simulation approach (Longstaff and Schwartz, 2001).

3.4 Relaxing assumptions to ensure ROA applicability

The main problem when transferring option theory to real problems is to ensure the restrictive assumptions of financial models. To relax these assumptions, we have adapted the original models at several points. First, since option valuation mainly considers market risks (Diepold et al., 2009), we integrated the product-related uncertainties of SHSs in the underlying valuation and its data generating process. To overcome the problem of the existence of perfect markets for options, we use valuation procedures that consider users' preferences, and we simulate their developments (Ullrich, 2013). Finally, we apply the LSM simulation to handle the assumption of fix expiration dates. With this method, it is possible to identify the right timing for IT investments, such as SHS switching, on the same basis as original option valuation models (Ullrich, 2013). Thus, we are able to interpret our results and use ROA for the application on our concrete decision situations to explain users' inertia in SHS switching decisions.

4 Solutions for Option Values and Optimal Timing

To find numerical solutions, we first determine variables to calculate the expected utilities of the option underlying. Second, we define simulation paths by following our presented stochastic differential equation. Based on concrete, random datasets, we then use the LSM simulation algorithm to derive the American-type values. We also calculate the European-type option values and compare them to the American-type ones to get a decision rule for optimal switching. Thus, we can show how to determine optimal timing to follow our first research goal. Finally, we examine the valuation effects of higher connectivity and their influences on optimal timing in order to answer the second research question.

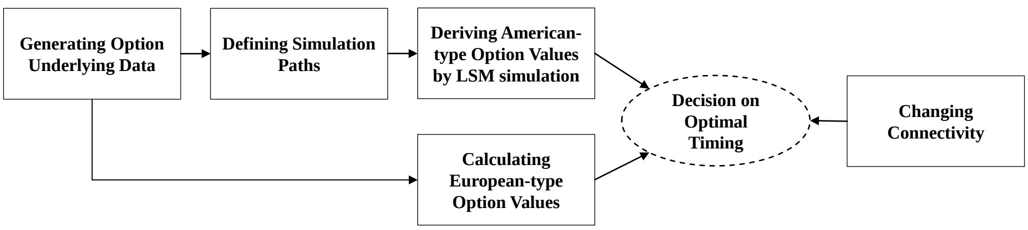

Figure 3. Structure of presented results.

4.1 Data generating processes and simulation paths

To solve our option valuation, we specify the utility functions (equation 4) as basis for the option underlying. We assume that CB_j and NB_j for both SHSs follow curves with diminishing marginal utilities when internal and exogenous network sizes increase. ln-functions are used to integrate that at least a network size of 2 is needed to generate utility. The valuation factors c_j and b_j are taken as random, multiplicative factors from a normal distribution. The exogenous network benefit is characterized by uncertainty about market success. If the new SHS is not adopted by other users, there will be no additional utility from network effects (Katz and Shapiro, 1994). Thus, we implement a failure probability f in the new SHS's utility indicating the user's expectations about its diffusion. We derive:

$$NB(b_j, N_j) = b_j * \ln(N_j) * x_j, \text{ with } P(x_2 = 1) = 1 - f \wedge P(x_2 = 0) = f \wedge x_1 = 1. \quad (8)$$

$$CB(c_j, DUC_j, H) = c_j * DUC_j * \ln(H). \quad (9)$$

Here, f, N_j, H, and DUC_j are fixed parameters. We assume $DUC_2 > DUC_1$, since we noted that the new SHS should be a superior alternative in terms of connectivity so that a denser home network is possible (for the concrete values of variables, see the Appendix). To reduce complexity and because we focus mainly on the internal connectivity, we keep external network sizes equal for both SHSs and differentiate NB_2 and NB_1 only concerning SHS 2's possible market failure. The stand-alone utilities A_2 and A_1 are again randomly drawn from a normal distribution. Finally, we use Monte Carlo simulation (1000 runs) and sum up the means of A_j, NB_j and CB_j to derive $E(U_j)$ for SHS 2 and SHS 1.

We then simulate the future development of $E(U_2)$ and $E(U_1)$ on 1000 simulation paths ($NS = 1000$) over the relevant time horizon to prepare to apply the LSM algorithm. Therefore, we define $T = 1$ as time to expiration and $NT = 365$ as number of time intervals. We assume that users could take their switching decision on every day within one year. To derive the processed values of $E(U_2)$ and $E(U_1)$ for every time interval, we use $E(U_2)$ and $E(U_1)$ as starting points in the first time interval and iteratively add $dE(U_j)$ for all other time intervals according to the geometric Brownian motion in equation 6. Thereby, we determine $\mu_{E(U_2)} > \mu_{E(U_1)}$ and $\sigma_{E(U_2)} > \sigma_{E(U_1)}$ to implement that SHS 2 is a better, but also more volatile alternative than SHS 1. We repeat the procedure for every simulation path. Thus, we derive two $NS \times NT$ simulation path matrices $\Theta_{E(U_1)}$ and $\Theta_{E(U_2)}$ that indicate the development of the underlying, with $E(U_2)$ and $E(U_1)$ as elements in the first columns.

4.2 Calculating option values and optimal timing

Longstaff and Schwartz (2001) formulate the following decision rule for LSM: at any incremental point of time within 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 (Longstaff and Schwartz, 2001). Thus, 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 are compared with immediate exercising to identify the right exercise decision along each simulation path. We repeat the procedure recursively for every exercise date (time interval) and can finally calculate the option value by discounting the net utility gains to time interval 1 (Moreno and Navas, 2003).

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

$$\Omega = \max(\Theta_{E(U_2)} - (\Theta_{E(U_1)} + K), 0). \tag{10}$$

The utility gains at expiration time (time interval NT, last column in matrix) are identical to utility gains of European-type options. 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. Analog to Longstaff and Schwartz (2001), we regress Y on a constant and different nonlinear functions (Laguerre Polynomials) of Z. Thus, we derive the estimated utility gains from option continuation conditional on $E(U_2)$ at time interval $NT-1$. If then the value of immediate exercise is greater than the value from continuation, it is better to exercise the option before expiration, otherwise it is optimal to exercise at T. For all simulation paths where the former relationship is true, we recursively repeat the procedure – least square regressions and value comparisons – until time interval $NT-(NT-2)$ (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 Ω. We then discount all the optimal utility gains back to the starting date. Finally, we derive the American-type option value w_{AM} with the discounted utility gains $\overline{UG}^*$ by

$$w_{AM} = (\sum_i^{NS} \overline{UG}_i^*/NS). \tag{11}$$

We run simulations of the underlying and the LSM algorithm five times in order to calculate w_{AM}. We also use equation 7 to calculate the European-type option value w_{EM} for every run. The optimal time interval t^* to switch is derived by searching the maximum averaged values of immediate exercising over all simulation paths for every time interval. We summarized the results with corresponding expected net present utilities in Table 1. The calculations provide numerical solutions for users' VoW and indicate when within the expiration period it is useful to switch SHSs. Thereby, we are able to explore to what extent users could benefit from different deferral strategies.

Run	w_{AM}	w_{EM}	t^*		$E(U_2)$	$E(U_1)$	$E(CB_2)$	$E(CB_1)$
1	**0.0312**	**0.0256**	**133**		165.30	157.61	34.87	20.92
2	**8.8263**	**6.0504**	**2**		173.08	144.21	34.46	20.68
3	**0.2127**	**0.1593**	**79**		162.48	149.67	34.46	20.67
4	**1.5359**	**1.4046**	**104**		176.91	156.76	34.74	20.85
5	**0.0007**	**0.0006**	**364**		157.32	156.81	34.49	20.70

Notation: $w_{AM/EM}$ ≙ American/European options value; t^* ≙ optimal timing; $E(U_j)$ ≙ expected net present utility of SHS j; $E(CB_2)$ ≙ expected net present connectivity-related utility of SHS j;

Table 1. Simulation results with $DUC_2 = 0.5$.

In all five presented runs American option values are higher than European ones. Thus, in these cases, it is valuable to switch to the new SHS before the expiration date. However, immediately switching systems in the home network is not the optimal strategy in nearly all runs. We can deduce a significant effect mechanism: the closer the valuations of both SHSs are, the better is it to wait and see before taking the decision. If there is a strong preference for SHS 2 in terms of expected net present utility (e.g. run 2), it could be more relevant to decrease the cost of deferral by switching immediately (here at time interval 2). We can confirm that option values are lower if the option is closer to expiry. Thus, users have to accept a trade-off between total SHS valuation (equation 5) and uncertainty reduction. Furthermore, we have derived cases in later simulation runs (with other seeds for the random number generator) where European option values are greater than the American ones ($w_{AM} = 0.7715$; $w_{EM} = 0.8865$; $t^* = 365$; $E(U_2) = 164.84$; $E(U_1) = 147.99$), or where the option values are equal to 0 ($w_{AM} = 0$; $w_{EM} = 0$; $E(U_2) = 133.09$; $E(U_1) = 143.99$). Thus, we conclude the following optimal decision mechanisms: first, if $w_{AM} > w_{EM}$, users should switch before the expiration date, which we also know owing to the condition's mathematical logic. The optimal point in time to which they should defer the actual action is defined by t^*. Second, if $w_{EM} > w_{AM}$ on the expiration date, users should wait until the option expires and should switch as late as possible with the lowest uncertainty. Finally, if $E(U_2) < E(U_1)$, users should not exercise the option and keep the incumbent SHS.

4.3 Influence of connectivity on VoW and timing decisions

We also shed light on connectivity's effects to answer the second research question. This analysis is especially relevant when systems are examined that are related to and used with other systems. Factors influencing these interdependencies can have important impacts on a switching decision's long-term success. Therefore, we increase the degree of connectivity of SHS 2 (DUC_2) exemplarily by 10%. We then examine changes for w_{AM}, w_{EM}, and t^*, ceteris paribus. To ensure comparability between lower-connectivity and higher-connectivity simulation runs, we use the same seeds for the random number generators of equal runs. Thereby, all effects on our target variables are only caused by another internal network density and not by, for instance, differing simulation paths (see new results in Table 2).

We observe that all real option values increase owing to the change in connectivity. Users have the opportunity to switch to a more valuable new SHS even if the utility gains are also more uncertain. The effect on optimal timing is twofold. For runs 1 and 3, it is better to defer the switching decision longer. For runs 4 and 5, we see an opposite result, since it is more effective to adopt SHS 1 earlier. The last observation can easily be explained by deferral costs. The higher $E(U_2)$ is, the higher is the loss of waiting to substitute SHSs. However, this effect mechanism does not hold true for runs 1 and 3. The difference in those cases is that w_{EM} has increased more strongly relative to w_{AM} with higher connectivity. Thus, later switching decisions are more favorable. We can explain this relationship by looking at expected future returns on $E(U_2)$ defined by the simulation path development. If the upward trend is more distinctive in later time intervals than in earlier ones, it is better to wait and to utilize the effects of higher connectivity at a point in time, where they are relatively more effective. In sum, we see that increased connectivity increases the option values and total SHS valuation. The influence on optimal timing, however, depends on when the additional utility effects come into play.

Run	w_{AM}	w_{EM}	t^*		$E(U_2)$	$E(U_1)$	$E(CB_2)$	$E(CB_1)$
1	**0.1068**	**0.1048**	**248**		168.79	157.61	38.36	20.92
2	**12.2526**	**8.8586**	**2**		176.53	144.21	37.91	20.68
3	**0.4889**	**0.4802**	**215**		165.93	149.67	37.90	20.67
4	**3.6899**	**2.7807**	**2**		180.38	156.76	38.22	20.85
5	**0.0057**	**0.0041**	**348**		160.77	156.81	37.94	20.70
Notation: $w_{AM/EM}$ ≙ American/European options value; t^* ≙ optimal timing; $E(U_j)$ ≙ expected net present utility of SHS j; $E(CB_2)$ ≙ expected net present connectivity-related utility of SHS j;								

Table 2. Simulation results with $DUC_2 = 0.55$.

5 Discussion and Implications

When new systems enter consumer markets, users often display inertia, which affects their switching behavior. Waiting before switching can then inform user decisions and can determine the right timing to take decisions. Therefore, it is critical to analyze the VoW, so that the effect of inertia on switching behavior and associated decisions mechanisms can be understood. To date, no approach has addressed the VoW concept to use it as an explanation for inertia in private users' technology management. Furthermore, we focus on new systems exhibiting possible interdependencies with other systems already used by users. Especially in the case of SHSs in private home networks, which are accompanied by significant product-related uncertainties, connections between systems can significantly influence usage behavior. Owing to switching decisions' intertemporal dependencies, we are able to apply ROAs to postulate a formal model representing the decision scenario. By concretizing a context-specific underlying in terms of a comprehensive SHS utility valuation, we provide a first model approach to analyze the role of deferring when substituting SHSs. Thus, we are able to analyze optimal timing of such switching decisions. We can also examine the influence of potentially uncertain product-related features, such as connectivity, in general. Thus, we cover the decision problem by forming a real option as combination of an American call option and an American put option. We use an LSM simulation to calculate numerical solutions with randomly generated data. Thereby, we show how to adapt an LSM approach to apply it to combined deferral/switching options.

The study's findings show significant effect mechanisms: first, the closer expected valuations of incumbent systems and new systems are, the better it is to defer a switching decision. When it is hard for users to say clearly which SHS is better, waiting and gaining more information helps to improve the decision. Users benefit from decision deferral, because the decisions they take can be less risky. Second, the higher the new SHS's expected utility gains are, the earlier users should switch, owing to deferral costs. This means that higher return anticipations can compensate for product-related uncertainties and foster diffusion processes. Furthermore, new systems' higher connectivity influences the right switching timing positively or negatively depending on when additional utility gains are more effective within the real option's expiration time. We can interpret this as follows: if users need more information to learn how to work with the possibilities of higher connectivity, they cannot exploit the advantages until a later stage in the decision process. Thus, it is valuable for users to wait, to maximize the effects of new systems' usage when they know better how to do it. However, if they can exploit the additional utility from increased connectivity immediately, it is better to switch sooner to reduce the costs of deferral.

Thus, we see that the utility-oriented underlying allows us investigating inertia in this concrete decision scenario. Together with our adapted and specifically defined real option model, the underlying's formalization differentiates our project's approach and helps to transfer ROA to a user perspective on the private management of digital technologies. The model and its development show that and explain why uncertainty reduction and timing aspects are relevant factors in switching decisions in home networks and beyond for cases of general system interdependencies. This study also contributes to IS switching theoretically by deriving concrete effect mechanisms of users' behavior and decision criteria from the model simulations.

Our findings also have practical relevance, especially concerning the timing of incentives. For instance, in the case of new system generations that are objectively better alternatives in terms of provided utility, incentive programs should be implemented shortly after market entry, since users will take switching decisions rather early. In the case of systems with high connectivity that are more complex to use, incentives should be combined with information campaigns. Thus, suppliers can reduce product-related uncertainties in advance and can help users to exploit new features' benefits earlier in the decision phase, so that switching can be accelerated. Thus, the right timing in switching decisions is also relevant for SHS suppliers, and the researched effect mechanisms in user behavior can have actual consequences for their product management.

6 Limitations and Future Research

The most critical limitation concerns model significance. To show relevance of option models, other studies usually work with field or quasi-field data, where actual numbers are realistically derived, or can at least be assumed quite well (Harmantzis and Tanguturi, 2007; Henseler and Roemer, 2013). In our study, since it is hard to predict and define exact utility values, we use randomly generated data to conduct the simulations. Future work could improve this process, for instance, by combining our model with empirical research in the form of conjoint analyzes, where it is possible to intuit relative importance and utilities of system features. Related to this, we show how we derived our results on a small number of simulation runs to see analyzing possibilities and our approach's significance. The next step would be to run a greater number of simulations to verify effect mechanisms via sensitivity analyzes on the basis of averaged values and thus to increase model generality. Furthermore, another limitation concerns the assumptions of our distinct option type. One important assumption is that we do not allow for switching back to the old SHS or for using both systems together in one network. Considering these decision possibilities would make the analysis even more realistic. Compound option valuation is one way to solve such sequential problems (Trigeorgis, 1996). However, combining our model with compound option approaches poses an even more complex modelling problem. Thus, future research could take our approach and extend it to consider aspects of compound real options.

We also see potential for future projects by examining the effects of simulation path developments. Even if geometric Brownian motions are utilized quite often for real option problems, they do not allow for varying volatilities and are thus weaker for modelling unexpected risks. One solution is to replace them by jump diffusion processes to integrate less predictable developments of utility returns in the simulation process (Kou, 2002; Longstaff and Schwartz, 2001). By comparing results between the different stochastic differential equations, we could further improve exact model specifications and model validity. Finally, we focus on the effects of internal connectivity on the optimal switching decision mechanisms. Thus, we exclude possible effects of exogenous network effects and their interactions with connectivity features within the home network. We will consider this aspect in future research, to get a comprehensive understanding of the decision situation. The relevance of the research project we have presented here will increase in the future, since upcoming systems and technologies are increasingly related and dependent on one another – not only in private usage situations, but also for fields such as digitized production processes, healthcare or traffic coordination.

References

Adner, R. and D. A. Levinthal (2004). "What Is Not A Real Option: Considering Boundaries for the Application of Real Options to Business Strategy." *Academy of Management Review* 29 (1), 74-85.

Bawa, K. (1990). "Modeling Inertia and Variety Seeking Tendencies in Brand Choice Behavior." *Marketing Science* 9 (3), 263-278.

Benaroch, M. (2002). "Managing Information Technology Investment Risk: A Real Options Perspective." *Journal of Management Information Systems* 19 (2), 43-84.

Benaroch, M. and R. J. Kauffman (1999). "A Case for Using Real Options Pricing Analysis to Evaluate Information Technology Project Investments." *Information Systems Research* 10 (1), 70-86.

Berger, M., C. Matt and T. Hess (2016). "Connectivity Is Ubiquitous, but Is it Beneficial? A Numerical Approach to Assess Individuals Valuations of Smart Home Systems." In*: Proceedings of the 49th Hawaii International Conference on System Sciences (HICSS)*. Kauai, Hawaii: USA, 1-10, forthcoming.

Bhattacherjee, A. (2001). "Understanding Information Systems Continuance: an Expectation-confirmation Model." *MIS Quarterly* 25 (3), 351-370.

Brenner, M. and M. G. Subrahmanyam (1994). "A Simple Approach to Option Valuation and Hedging in the Black-Scholes Model." *Financial Analysts Journal* 50 (2), 25-28.

Burnham, T. A., J. K. Frels and V. Mahajan (2003). "Consumer Switching Costs: A Typology, Antecedents, and Consequences." *Journal of the Academy of Marketing Science* 31 (2), 109-126.

Carr, P. (1995). "The Valuation of American Exchange Options with Applications to Real Options." In: *Real Options in Capital Investment - Models, Strategies, and Applications.* Ed. by L. Trigeorgis. Westport, Connecticut, London: Praeger, 109-120.

Chen, P.-Y. and L. M. Hitt (2002). "Measuring Switching Costs and the Determinants of Customer Retention in Internet-Enabled Businesses: A Study of the Online Brokerage Industry." *Information Systems Research* 13 (3), 255-274.

Copeland, T. and V. Antikarov (2001). *Real Options - A Practitioner's Guide.* New York: Texere.

Diepold, D., C. Ullrich, A. Wehrmann and S. Zimmermann (2009). "A Real Options Approach for Valuating Intertemporal Interdependencies within a Value-based IT Portfolio Management - A Risk-return Perspective." In*: Proceedings of the 19th European Conference on Information Systems (ECIS)*. Verona: Italy, Paper 244.

Dimoka, A., Y. Hong and P. A. Pavlou (2012). "On Product Uncertainty In Online Markets: Theory And Evidence." *MIS Quarterly* 36 (2), 395-426.

Dong, D. and A. Saha (1998). "He Came, He Saw, (and) He Waited: an Empirical Analysis of Inertia in Technology Adoption." *Applied Economics* 30 (7), 893-905.

Dos Santos, B. L. (1991). "Justifying Investments in New Information Technologies." *Journal of Management Information Systems* 7 (4), 71-89.

Farrell, J. and G. Saloner (1985). "Standardization, Compatibility, and Innovation." *The RAND Journal of Economics* 16 (1), 70-83.

Goswami, S., H. H. Teo and H. C. Chan (2008). "Real Options from RFID Adoption: the Role of institutions and Managerial Mindfulness." In*: Proceedings of the 29th International Conference on Information Systems (ICIS)*. Paris: France, Paper 128.

Gupta, S., N. E. Hong and H.-W. Kim (2007). "Online Customer Retention: The Resistance to Change Perspective." In*: Proceedings of the 28th International Conference on Information Systems (ICIS)*. Montreal: Canada, Paper 137.

Haenlein, M., A. M. Kaplan and D. Schoder (2006). "Valuing the Real Option of Abandoning Unprofitable Customers When Calculating Customer Lifetime Value." *Journal of Marketing* 70 (3), 5-20.

Harmantzis, F. C. and V. P. Tanguturi (2007). "Investment Decisions in the Wireless Industry Applying Real Options." *Telecommunications Policy* 31 (2), 107-123.

Heinrich, B., A. Huber and S. Zimmermann (2011). "Make and Sell or Buy of Web Services a Real Option Approach." In*: Proceedings of the 19th European Conference on Information Systems (ECIS)*. Helsinki: Finland, Paper 90.

Henseler, J. and E. Roemer (2013). "'Let's Wait and See!' The Real Option to Switch as a New Element of Customer Value." *Schmalenbach Business Review* 65 (2), 112-136.

Herbrechter, M., B. Ley and M. Stein (2011). "Kontextsensitive Service-Infrastruktur für die mobile Nutzung von Home-IT." In*: Proceedings of the 10th International Conference on Wirtschaftsinformatik*. Zurich: Switzerland, 1012-1021.

Hoppe, H. C. (2002). "The Timing of New Technology Adoption: Theoretical Models and Empirical Evidence." *The Manchester School* 70 (1), 56-76.

Ji, Y. (2010). "Incorporating Knowledge Building in Real Options Analysis of Technology Project Investment." In*: Proceedings of the 31th International Conference on Information Systems (ICIS)*. Saint Louis: USA, Paper 268.

Katz, M. L. and C. Shapiro (1994). "Systems Competition and Network Effects." *Journal of Economic Perspectives* 8 (2), 93-115.

Kauffman, R. J. and X. Li (2005). "Technology Competition and Optimal Investment Timing: a Real Options Perspective." *IEEE Transactions on Engineering Management* 52 (1), 15-29.

Khan, U. and M. B. Stinchcombe (2015). "The Virtues of Hesitation: Optimal Timing in a Non-Stationary World." *The American Economic Review* 105 (3), 1147-1176.

Kim, H.-W. and A. Kankanhalli (2009). "Investigating User Resistance to Information Systems Implementation: a Status Quo Bias Perspective." *MIS Quarterly* 33 (3), 567-582.

Kou, S. G. (2002). "A Jump-diffusion Model for Option Pricing." *Management science* 48 (8), 1086-1101.

Kulatilaka, N. and L. Trigeorgis (1994). "The General Flexibility to Switch: Real Options Revisited." *International Journal Of Finance* 6 (2), 778-798.

Kumar, R. L. (1996). "A Note on Project Risk and Option Values of Investments in Information Technologies." *Journal of Management Information Systems* 13 (1), 187-193.

Li, X. (2009). "Preemptive Learning, Competency Traps, and Information Technology Adoption: A Real Options Analysis." *IEEE Transactions on Engineering Management* 56 (4), 650-662.

Longstaff, F. A. and E. S. Schwartz (2001). "Valuing American Options by Simulation: a Simple Least-squares Approach." *Review of Financial Studies* 14 (1), 113-147.

Loraas, T. and C. J. Wolfe (2006). "Why Wait? Modeling Factors that Influence the Decision of When to Learn a New Use of Technology." *Journal of Information Systems* 20 (2), 1-23.

Margrabe, W. (1978). "The Value of an Option to Exchange One Asset for Another." *The Journal of Finance* 33 (1), 177-186.

Matutes, C. and P. Regibeau (1996). "A Selective Review of the Economics of Standardization. Entry Deterrence, Technological Progress and International Competition." *European Journal of Political Economy* 12 (2), 183-209.

McDonald, R. and D. Siegel (1986). "The Value of Waiting to Invest." *The Quarterly Journal of Economics* 101 (4), 707-728.

Moreno, M. and J. F. Navas (2003). "On the Robustness of Least-Squares Monte Carlo (LSM) for Pricing American Derivatives." *Review of Derivatives Research* 6 (2), 107-128.

Polites, G. L. and E. Karahanna (2012). "Shackled to the Status Quo: the Inhibiting Effects of Incumbent System Habit, Switching Costs, and Inertia on New System Acceptance." *MIS Quarterly* 36 (1), 21-42.

Rumelt, R. P. (1995). "Inertia and Transformation." In: *Resource-Based and Evolutionary Theories of the Firm: Towards a Synthesis.* Ed. by C. Montgomery. Springer US, 101-132.

Samuelson, W. and R. Zeckhauser (1988). "Status Quo Bias in Decision Making." *Journal of Risk and Uncertainty* 1 (1), 7-59.

Saya, S., L. G. Pee and A. Kankanhalli (2010). "The Impact of Institutional Influences on Perceived Technological Characteristics and Real Options in Cloud Computing Adoption." In*: Proceedings of the 31st International Conference on Information Systems (ICIS)*. St. Louis: USA, Paper 24.

Schwartz, E. S. and C. Zozaya-Gorostiza (2003). "Investment Under Uncertainty in Information Technology: Acquisition and Development Projects." *Management Science* 49 (1), 57-70.

Sollars, G. G. and S. A. Tuluca (2012). "The Optimal Timing of Strategic Action–A Real Options Approach." *Journal of Entrepreneurship, Management and Innovation* 8 (2), 78-95.

Trigeorgis, L. (1996). *Real Options: Managerial Flexibility and Strategy in Resource Allocation.* Cambridge: MIT Press.

Ullrich, C. (2013). "Valuation of IT Investments Using Real Options Theory." *Business & Information Systems Engineering* 5 (5), 331-341.

Venkatesh, A. (2008). "Digital Home Technologies and Transformation of Households." *Information Systems Frontiers* 10 (4), 391-395.

Ye, C. and R. Potter (2011). "The Role of Habit in Post-adoption Switching of Personal information Technologies: an Empirical Investigation." *Communications of the Association for Information Systems* 28 (1), 585-610.

Appendix

Values for variables in underlying data generation				
$N_{2/1} = 300$	$H_{2/1} = 300$	$DUC_2 = 0.5$	$DUC_1 = 0.3$	$f = 0.3$
Values for variables in option calculation				
$\gamma = 0.05$	$r = 0.03$	$K = 20$	$\sigma^2 = \sigma_2^2 + \sigma_1^2 - 2\sigma_2\sigma_1\rho = 0.04^2 + 0.01^2 - 2 * 0.04 * 0.01 * 0.1$	