Path dependence in two-sided markets

A simulation study on technological path dependence
with an application to platform competition in the smartphone industry

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In the world of QWERTY one cannot trust markets to get it right.

—Paul Krugman, *Peddling Prosperity*

Danksagung

Biographien verlaufen pfadabhängig, so sagt man. Dagegen spricht, dass die Promotion, nun ein Teil meiner Biographie, statt zu einer Verfestigung vielmehr zu einer Weitung des Wissens-, Erfahrungs- und Möglichkeitsraums beigetragen hat. Ich bin sehr dankbar dafür, dass ich diese Chance wahrnehmen konnte.

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List of abbreviations

ABM	Agent-based modeling
ABMS	Agent-based modeling and simulation
ABS	Agent-based simulation
ACE	Agent-based computational economics
API	Application programming interface
App	Software application (for a smartphone)
CAS	Complex adaptive systems
DoE	Design of experiments
DSK	Dvorak simplified keyboard
DVD	Digital versatile disc
HHI	Herfindahl-Hirschman index
LCK1	1^{st} degree lock-in
LCK2	2^{nd} degree lock-in
LCK3	3^{rd} degree lock-in
MABS	Multi-agent based simulation
MSP	Multi-sided platform
NLS	Nonlinear least squares
ODD	Overview, design concepts, details (ODD protocol)
OLI	Oligopoly state
OS	Operating system
PC	Personal computer
PDA	Personal digital assistant
PDF	Portable document format
SD	Standard deviation
VCR	Video cassette recorder
VHS	Video home system

1 Introduction

Research on competing technologies lies at the very heart of path dependence theory, which emphasizes the notion of 'small events' and self-reinforcing mechanisms to explain stability in various organizational, technological and institutional settings. Despite the theory's broad range of applications, the phenomenon of technological lock-ins, in which a sub-optimal, or *inferior*, technology dominates the market for a long period of time, still remains the most obvious and intriguing example for path dependence.

Four types of self-reinforcing mechanisms are considered to be the driving force for the occurrence of technological lock-ins: supply-side economies of scale, learning effects, adaptive expectations as well as direct and indirect network effects. However, the most prominent empirical cases for the illustration of technological path dependence all highlight the key role of indirect network effects. As such, the prevalence of the QWERTY keyboard, the victory of *VHS* over *Betamax* as well as the dominance of *Microsoft Windows* in the PC industry emphasize the severe consequences of self-reinforcing indirect network effects for the development of technological paths. All of these empirical cases evolved in market settings where different groups of economic actors interact through a technology platform and mutually provide each other with indirect network effects. Recent research on network markets refers to these settings as 'two-sided markets'. This concept provides an actor-centric view of indirect network effects, highlighting both the interactions between two sets of agents, as well as the interdependence of their decisions. With this holistic perspective on indirect network effects, the concept of two-sided markets offers a valuable complement to the study of technological path dependence.

However, despite the vast body of theoretical and empirical research based on David's (1985), Katz and Shapiro's (1985) and Arthur's (1989) seminal works, we still know very little about the conditions under which network markets tend to lock in to inferior technology platforms. Due to a vague conceptualization of inefficiency, Arthur's prominent model of competing technologies (Arthur 1989) falls short of explaining lock-ins to *inferior* technologies — which, however, is the essence of path dependence theory. Since these early contributions, case study research has played a major role in advancing the field by illustrating the long-term dominance of a particular technological standard despite the existence of superior alternatives. So far, these historical case-by-case analyses have concentrated on explaining specific path-dependent trajectories, but have failed to provide general insights. Hence, neither theoretical contributions nor empirical research have yet been able to draw precise conclusions as to why and under which circumstances network markets tip towards an inferior technology.

This dissertation addresses this research gap and raises the following research question: *What are the conditions under which two-sided markets with indirect network effects become locked-in to an inferior technology platform?* Focusing on potential context- and actor-specific factors of influence, this study analyzes (1) the relative strength of indirect network effects and differences in platform quality, (2) the role of imperfect information and bounded rationality, (3) the influence of switching behavior and (4) the effect of synergies that facilitate 'multi-homing' strategies.

Much research on technological path dependence has so far relied on contributions from qualitative research, with a strong focus on historical case studies. However, prominent scholars have raised epistemological concerns against this methodological bias and recommend the application of more controlled research designs. The dissertation follows this call and develops an agent-based simulation model for investigating platform competition and path dependence in two-sided markets. Simulation research is particularly well suited for tracing the complex mechanisms of unfolding lock-in processes over time. In addition to exploring the impact of contingent 'small events' in otherwise identical conditions, simulations can be re-run multiple times with varied system parameters to generalize about the underlying mechanisms. By allowing for more realistic assumptions such as boundedly-rational behavior, agent-based models help to overcome the dichotomy between real-world complexity and the oversimplified abstraction level of analytical models.

External validity remains one of the primary weaknesses of simulation research. The present study addresses this criticism and places great emphasis on the empirical (micro-)validation and calibration of the proposed model. For this purpose, the simulation model is applied to the global smartphone industry, and calibrated on the basis of quantitative and qualitative empirical data gathered by means of a conjoint study, qualitative interviews and press analyses. The smartphone market is a very recent example of a 'standards battle' which involves indirect network effects. Despite its rapidly growing social and economic importance, little scientific research has been conducted on this industry. Apart from the high relevance of this empirical case, the study's forward-looking perspective on an emerging industry adds a new dimension to research on technological path dependence, which has so far concentrated on retrospective cases.

The thesis is structured as follows. Following a thorough review of the theoretical literature on technological path dependence in chapter 2, the research question is derived and further refined by outlining potential factors of influence that provide the focus of this study (chapter 3). Chapter 4 explains the choice of agent-based simulation for this research project, highlighting the unique benefits of the chosen methodological approach in comparison to alternative research designs. A conceptual model of competing technologies and path dependence in the context of the classic 'hardware/software paradigm' is then presented in chapter 5. Chapter 6 provides the reader with a background of the emerging smartphone industry, which is used for the empirical (micro-)validation and calibration of the simulation model in chapter 7. Chapter 8 describes the design of experiments and discusses the simulation results. The final chapter highlights the theoretical and practical implications of the findings, explores avenues for further research and summarizes the contribution of this dissertation.

2 Theoretical background

Path dependence is a widely used concept in the social sciences to explain stability in various organizational, technological and institutional settings. Path dependence theory stresses the importance of 'small events' which are magnified over the course of time by positive feedback mechanisms, resulting in a potentially inefficient 'lock-in' state.

The notion of path dependence has been fruitfully applied at the macro, meso and micro levels (Vergne & Durand 2010). At the macro level, path dependence addresses harmful institutional persistence with regard to economic development (North 1990) and political processes (Pierson 2000). At the meso level, path dependence is used to explore the persistent dominance of inferior technologies (David 1985; Arthur 1989) and governance structures (Williamson 1999). At the micro level, path dependence serves as a "surrogate for organizational rigidity" (Vergne & Durand 2010, p. 737) and focuses on organizational capabilities and resources to explain inertia in changing environments (Schreyögg & Kliesch-Eberl 2007; Sydow et al. 2009).

Given its broad scope of application, path dependence has become a mainstream construct in the social sciences. However, despite its popularity[1], there is no consensus within the scientific community regarding a concise definition of path dependence (Sydow et al. 2009; Ackermann 2001).[2] Many scholars employ a rather metaphorical 'history matters' understanding. In this view, path dependence is little more than a label for the obvious: social processes are self-referential in the sense that former decisions influence those that follow (Sydow et al. 2005). Others conceive of path dependence as a synonym for persistence and hence confuse process with outcome. As a result, path dependence is at risk of being regarded as a ubiquitous but vague phenomenon and losing its distinct explanatory value. In addition, the

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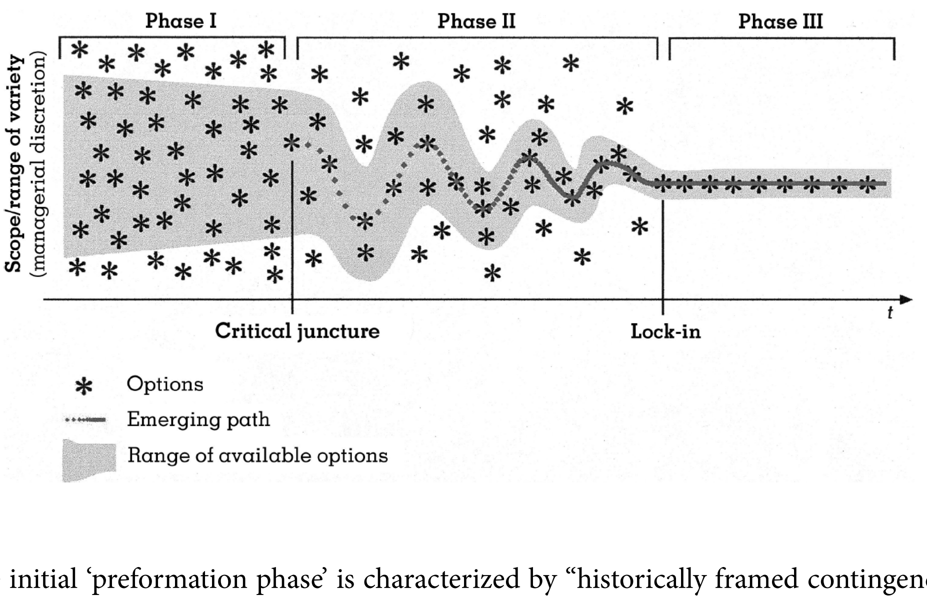
1 Inspired by Sydow et al. (2009), Vergne & Durand (2010) conduct a database search within seven preeminent organization and management journals (*Academy of Management Journal*, *Academy of Management Review*, *Administrative Science Quarterly*, *Journal of Management Studies*, *Organization Science*, *Organization Studies* and *Strategic Management Journal*). Between 2003 and 2007, 214 articles directly refer to the concept of path dependence, equal to 10.5 percent of all articles published.

2 For instance, see David (1997, pp. 13-19) for a thorough discussion of various formal definitions of path dependence in the economic literature.

theoretical argument of path dependence is often not clearly distinguished from related concepts. The organizational imprinting literature, for instance, also stresses the relevance of initial conditions (Stinchcombe 1965). Likewise, population ecology has proposed the notion of structural inertia to explain stability of organizational arrangements, acknowledging both its beneficial and adverse effects (Hannan & Freeman 1984). In the field of technology diffusion, the market dominance of inferior technologies has been attributed to first-mover advantages arising from learning effects, preemption of input factors and switching costs (Lieberman & Montgomery 1988). In light of the conceptual proximity, path dependence theory needs to clearly emphasize its distinct benefits in terms of explanatory value as opposed to other related concepts.

In order to unleash the full potential of the construct, some scholars have recently highlighted the need for a more narrow conception of path dependence. With a focus on organizational path dependence, Sydow et al. (2009) define path dependence as a "rigidified, potentially inefficient action pattern built up by the unintended consequences of former decisions and positive feedback processes" (Sydow et al. 2009, p. 696). They propose a phase model of path dependence that emphasizes the different structural properties and causal regimes in three distinct stages of the path formation process (Figure 2-1).

Figure 2-1 **The "Berlin model": constitution of an organizational path**
(Source: Sydow et al. 2009, p. 692)



The initial 'preformation phase' is characterized by "historically framed contingency" (Sydow et al. 2009, p. 693). In this open situation with a broad scope of action, seemingly insignificant "small events" (Arthur 1989, p. 117) trigger a self-reinforcing process. This critical juncture marks the transition to the 'formation phase'. In this second stage, the initial decisions of the prior phase are magnified over time by self-reinforcing processes that gradually restrict the scope of action. The final 'lock-in phase' represents a stable equilibrium where the path is replicated and "alternative courses of action are no longer feasible" (Sydow et al. 2009, p. 694). By proposing this phase model, Sydow et al. provide an explanatory framework as well as an operational tool for research on organizational path dependence.

With similar objectives to Sydow et al. (2009) but with less focus on organizational matters, Vergne & Durand (2010) aim to provide conceptual clarification of the "blurred" notion of path dependence. The authors offer a formal definition and identify necessary conditions for path dependence. Following Vergne & Durand, I define path dependence as the "property of a stochastic process which obtains under two conditions (contingency and self-reinforcement) and causes lock-in in the absence of exogenous shock" (Vergne & Durand 2010, p. 737). As emphasized by this definition, path dependence describes a particular *class of processes* instead of an *outcome*.

The present chapter provides an introduction to the notion of technological path dependence[3] and is structured as follows. First, I review the seminal works by Paul David and Brian Arthur that established the foundations of path dependence theory. The properties of path-dependent processes are discussed, followed by an account of the prominent critique by Liebowitz & Margolis (1990, 1995) centering around inefficiency and market failure. Subsequently, I elaborate on the terms included in the proposed definition of path dependence (i.e., contingency, self-reinforcement and lock-in). Here I also discuss the different types of self-reinforcing mechanisms in the field of technology diffusion, with particular attention devoted to indirect network effects. Lastly, the closely related concept of two-sided markets is presented, which offers a holistic perspective on 'platform competition' in markets subject to indirect network effects.

[3] As this dissertation focuses on technological paths, the theoretical introduction deliberately omits the related literature on organizational or institutional paths. Please refer to Sydow et al. (2009) and Vergne & Durand (2010, pp. 738-741) for a thorough overview of both streams of literature.

2.1 Technological path dependence

Research on competing technologies is at the very core of path dependence theory (David 1985; Arthur 1989). Despite a growing stream of literature on organizational path dependence, the case of market dominance of an inferior technology remains the most obvious and intriguing argument for path dependence. Various examples of this have been raised to provide empirical evidence for the notion of technological paths. For instance, technological lock-ins have been explored in the realms of keyboard layouts (David 1985), nuclear power technology (Cowan 1990) and home-video standards (Cusumano et al. 1992). Among these works, the case of the QWERTY keyboard layout is an omnipresent example. Therefore, I shall begin to elaborate the theoretical foundations by starting with this most prominent case of technological path dependence.

2.1.1 David's economics of QWERTY

In a narrative study of economic history, David (1985) explores the dominance of the QWERTY keyboard layout despite the existence of technically more efficient alternatives. His contribution provided the impetus for path dependence research. It is widely regarded as a critique of neoclassical economic thinking, as it breaks with two central assumptions:[4] first, David addresses how "historical accidents" (David 1985, p. 332) can be responsible for irreversible economic processes; second, he questions whether decentralized decision-making necessarily results in the optimal[5] technology being chosen by 'the market'. The illustration of the QWERTY case below follows the original paper by David (1985).

Early versions of the typewriter, which was invented in the second half of the 19th century, suffered from the problem that type bars would clash and jam when keys were struck in rapid succession. To mitigate this behavior, the engineers rearranged the key ordering to reduce the frequency of type bar clashes. As a result of trial-and-error modifications by Christopher

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4 However, David emphasizes that his story is meant to be "simply illustrative and does not establish how much of the world works this way" (David 1985, p. 332).

5 As will be shown, the meaning of 'optimal' deserves special attention. Section 2.1.4 discusses in detail the difference between technical and economic efficiency criteria and the implications for path dependence theory.

Sholes between 1867 and 1873, the initial alphabetical key ordering of the first typewriter machine was replaced by the QWERTY layout, named after the topmost row of letters on the keyboard. In addition to its benefit in terms of fewer type bar clashes, the QWERTY layout was also a “sales gimmick” (David 1985, p. 333). The upper row of the keyboard includes all the letters necessary to quickly type the word ‘TYPEWRITER’, also the brand name of the machine — an intriguing feature which was often utilized by salesmen to impress customers. After the manufacturing rights were granted to *E. Remington & Sons*, the QWERTY layout became commercially popular with the *Remington No. 2* machine in 1878.

However, the technical necessity for the QWERTY layout quickly vanished. As early as the 1880s, improved typewriter designs were replacing type bars in favor of a cylindrical typewheel, which eliminated the problem of jamming type bars. These new devices were released with modified keyboard arrangements “more sensible than QWERTY” (David 1985, p. 334). For instance, *Blickensderfer*'s ‘Ideal’ keyboard from 1893 placed the ten most commonly used letters in the English language (‘DHIATENSOR‘) in the center row to increase efficiency. Over the following decades, several improved keyboard layouts were proposed. Most prominent was the *Dvorak Simplified Keyboard* (DSK), which was developed on the basis of human physiology and letter frequencies in the English language. It was found to be superior to the QWERTY keyboard in terms of typing speed, error rates, training time and comfort by a U.S. Navy study in 1944, although some scholars question the rigor of the study (Liebowitz & Margolis 1990).

To summarize, the original rationale for the QWERTY layout quickly became irrelevant due to technological progress in typewriter design — and disappeared entirely after typewriters were replaced by personal computers. Furthermore, a number of superior keyboard layouts with distinct advantages were proposed over the course of time. Despite these developments, the QWERTY keyboard gained further adoption and is today, with minor regional modifications, the de-facto standard worldwide.[6] What are the reasons for the intriguing dominance of this inferior technology for more than 100 years?

David attributes this effect, which he refers to as “lock-in” (David 1985, p. 335), to the dynamics of a complex system of interrelated actors. Among these actors are the manufacturers

[6] Interestingly, the QWERTY standard has also been adopted for non-Latin script. For instance, QWERTY-like layouts are widely used for Cyrillic and East Asian languages (cf. Abbasov et al. 2009; Khan et al. 2006).

and buyers of typewriters, professional typists as well as training providers that teach touch-typing skills. Three features of the system contributed to the prevalence of the QWERTY standard: (1) technical interrelatedness, (2) economies of scale and (3) quasi-irreversibility of investment.

Technical interrelatedness[7] refers to the need for hardware/software compatibility between the keyboard layout ('hardware') and the touch-typing skills of typists ('software'), which is based on the specific key arrangement that was memorized during training. For a company, the value of a typewriter depended on the availability of typists trained for that particular keyboard layout. Therefore, a business firm was more willing to choose QWERTY typewriter models, for which many professional typists had already been trained. In turn, higher sales numbers of QWERTY typewriters induced more professional typists to learn to operate this keyboard in order to increase their employability.

This technical interrelatedness forms the basis for *economies of scale*. David (1985) argues that the increase in the number of QWERTY-trained typists led to lower wages, which contributed to a decrease in firms' overall costs for maintaining a QWERTY typewriting system. In addition, training providers also incurred lower costs when training typists on a single (QWERTY) keyboard layout, as they did not need to invest in alternative typewriter models.

Lastly, the lock-in was reinforced by the *quasi-irreversibility of investment* arising from the nature of learning and habituation. This refers to the high switching costs of retraining typists on an alternative keyboard layout.

In summary, David argues that "historical accidents" (David 1985, p. 335) in combination with positive feedback mechanisms "drove the industry prematurely into standardization on the wrong system" (David 1985, p. 336). QWERTY gained an initial lead in adoption through its association with the popular *Remington* typewriter model. This "quantitatively slender" (David 1985, p. 335) advantage was then magnified over the course of time by the effects of technical interrelatedness, economies of scale and the quasi-irreversibility of investment. David introduces the term 'path-dependent' to describe this type of process in

[7] This feature of the system will be covered in detail in the discussion on indirect network effects. The notion of 'network economics' became popular around the same time as the original QWERTY paper. In fact, David (1985) gives reference to an early version of the seminal paper on network effects by Katz & Shapiro (1985). See also Farrell & Klemperer (2007, pp. 2011-2013) for an account of the role of network effects that enforced QWERTY's dominance.

which "temporally remote events, including happenings dominated by chance elements rather than systematic forces" (David 1985, p. 332) affect the outcome. In these nonergodic stochastic processes, several outcomes are possible and transient factors in the beginning of the process *irreversibly* determine which path will be taken. David concludes with a remark that he believes "there are many more QWERTY worlds lying out there" (David 1985, p. 336) and that economic analysis needs to focus on "essentially historical dynamic processes" (David 1985, p. 336) in order to better understand technological path dependencies.

2.1.2 Arthur's model of competing technologies

David's qualitative account of the QWERTY case is taken up by a prominent model of Brian Arthur (1989) on the role of increasing returns for the occurence of technological lock-ins. Arthur's important contribution helped to formalize the concept of path dependence and clarified major terms and conditions. The presentation of the model design and model behavior sets the scene for a thorough discussion of the properties of path-dependent processes in section 2.1.3. The description of the model follows the original paper by Arthur (1989).

In Arthur's dynamic analysis of two competing technologies, a (infinitely) large number of agents are assumed to adopt either technology A or B.[8] Each individual choice is irrevocable, i.e., agents cannot switch to another technology later on. Agents are of two types, R and S, and are equal in numbers. Table 2-1 shows their payoff function when choosing either technology A or B.

Table 2-1 **Payoff function in Arthur's model of competing technologies**
(Source: Arthur 1989, p. 118)

	Returns to choosing	
	Technology A	*Technology B*
R-type agent	$a_R + r\, n_A$	$b_R + r\, n_B$
S-type agent	$a_S + s\, n_A$	$b_S + s\, n_B$

8 Neither of the abstract technologies is 'sponsored'; accordingly they are not strategically priced or manipulated by any firm.

It is assumed that R-type agents have a natural preference for A, whereas S-type agents have a natural preference for B. Hence, $a_R > b_R$ and $a_S < b_S$. Apart from their natural preference, agents are also influenced in their choice by the number of previous adopters of the respective technology, expressed by n_A and n_B. The direction of influence depends on the "returns regime" (Arthur 1989, p. 119). Under constant returns ($r, s = 0$), the payoffs are unaffected by the number of other adopters. Under increasing returns ($r, s > 0$), both technologies yield higher payoffs the more they are adopted, for instance because of network effects or economies of scale in production.[9] Under diminishing returns ($r, s < 0$), the attractiveness of the technologies decrease with greater adoption. This case follows the traditional neoclassical assumption that markets "eventually run into limitations" (Arthur 1996, p. 100), for instance due to scarce input factors that drive prices.

The agents enter the market successively and in random order (for instance, R-S-S-R-S-R-R-S). Accordingly, the sequence in which agents make their choice is unknown ex-ante and is determined by randomly occurring "small events" (Arthur 1989, p. 118), which are outside the scope of the model. Given this setup, Arthur analyzes the allocation process under the three different returns regimes.

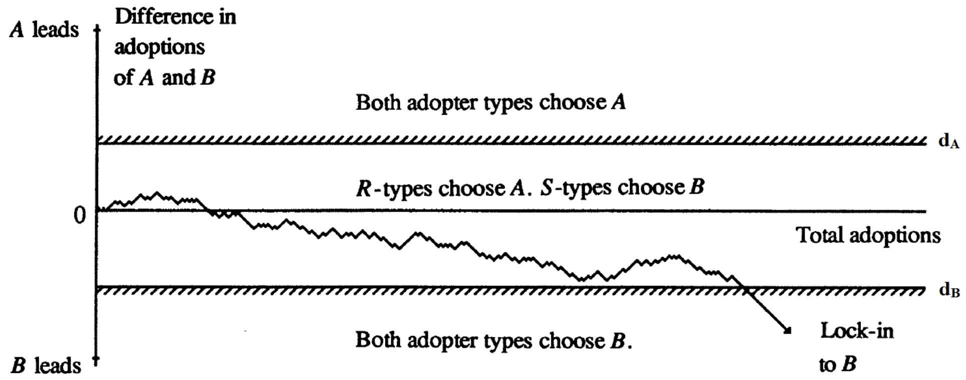
In the case of constant returns to adoption, both types of agents always choose their preferred technology, regardless of the adoption behavior of other agents. Given that the agents' order of entry, and thereby the choice order, is random, any technology can experience a *temporary* advantage in market share. However, in the long run, both technologies split the market 50:50, given equal numbers of R-type and S-type agents. The small events that randomly determine the choice sequence are "averaged away" (Arthur 1989, p. 117).

Under increasing returns to adoption, agents choose their preferred technology *except for* the case that the other technology is — by chance — ahead by a certain number of adopters. In the latter situation, R-type agents choose technology B despite their natural preference for A.

9 Arthur does not further specify the source of increasing returns in his early contribution, apart from a comment that "the more they [technologies] are adopted, the more experience is gained with them, and the more they are improved" (Arthur 1989, p. 116). Nonetheless, Arthur elaborates on the sources of increasing returns in his later work (Arthur 1994). The underlying mechanisms for increasing returns in the technology context will be covered in detail in section 2.1.5.2.

The reverse holds for S-type agents. The resulting adoption process is a random walk with absorbing barriers, as shown in Figure 2-2.

Figure 2-2 **Adoption under increasing returns: a random walk with absorbing barriers**
(Source: Arthur 1989, p. 120, with minor additions)



In the beginning, the adoption of technology A and B is completely determined by the random choice sequence of the two types of agents. R-type agents choose A, and S-type agents choose B. Both agent types are equally likely. As a result, the adoption process appears as a random walk with each step towards technology A ('up') or B ('down') having an equal probability of 0.5. However, if *by chance* a number of S-type agents enter the market in a row (for instance, R-S-S-S-S-S-S-S), technology B gains a distinct advantage in market share. In this case, the lead of technology B in terms of adopters outweighs R-type agents' natural preference for A, so that $r(n_B - n_A) > a_r - b_R$. Both agent types now choose technology B, which further increases its lead. The same holds for the other direction if technology A is ahead in adoption. In both cases, the process "is 'locked in' to one technology only" (Arthur 1989, p. 121). The lock-in occurs if the random walk exceeds the upper barrier d_A or falls below the lower barrier d_B, which are described by:

$$d_A = n_A - n_B = \frac{(b_S - a_S)}{s},$$
$$d_B = n_A - n_B = \frac{(b_R - a_R)}{r}.$$

Under increasing returns, both barriers are *absorbing*: once they are reached, the process is pushed further towards the outer regions.[10] From this point, the random walk becomes a deterministic process that locks in. The magnitude of increasing returns is expressed by the values of r and s. Higher values of r and s decrease the distance between the barriers and thus increase the probability of lock-in.

Under diminishing returns to adoption, agents choose their preferred technology except for the case that their preferred technology is ahead of the other by a certain number of adopters. For instance, if by chance technology A gains a distinct advantage in market share, R-type agents will choose B despite their natural preference for A. The reverse holds for technology B. Under diminishing returns, both barriers are *reflecting*: once they are reached, the process is pushed back towards the center region. Similar to the constant returns case, in the long run both technologies split the market 50:50, given equal numbers of R-type and S-type agents. The choice sequence thus has no permanent impact.

This comparison of the three returns regimes reveals that a lock-in only occurs in the case of increasing returns, in which one technology comes to completely dominate the market. Furthermore, it is only under the conditions of increasing returns that random, small events are critical for the outcome of the adoption process: the nonergodic process is "determined by its small-event history" (Arthur 1989, p. 122) and is thus *path-dependent*. As a result, the increasing returns case has distinct properties that deserve particular attention. By referring to Arthur's model, I shall now elaborate on these properties of path-dependent processes.

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[10] To avoid confusion, it should be noted that the random walk process can freely approach the absorbing barrier from the inner region. As such, the barrier is absorbing from one side (the outer regions) only. Arthur's increasing returns model can also be illustrated by a narrow plateau with steep drop offs on both sides, representing the two absorbing barriers. In this setting, taking a random step to the left or right has no long-term effects as long as one stays safely on the plateau. However, moving (by chance) too far to the left or right has irrevocable consequences.

2.1.3 Properties of path-dependent processes

Arthur describes four properties of 'path-dependent' processes: unpredictability, inflexibility, nonergodicity and potential path-inefficiency.[11] Arthur's account of these four properties is of great value to path dependence theory, as he was the first scholar to systematically explore and formally describe the nature of path-dependent processes. The four properties are discussed below.

2.1.3.1 Unpredictability

A path-dependent process is *unpredictable* because its outcome is determined by random, small events early on in the process.[12] Referring to Arthur's model, the result of the adoption process is unknown ex-ante: one does not know whether technology A or B will dominate the market since the outcome depends on the random choice sequence of the agents. However, given that in the long run an "absorbing random walk eventually crosses the barrier with probability one" (Arthur 1989, p. 121), lock-in to one of the technologies will occur *with certainty*.[13] The two technologies "cannot coexist indefinitely" (Arthur 1989, p. 121).

2.1.3.2 Inflexibility and lock-in

A path-dependent process is *inflexible* in the sense that it cannot be influenced by marginal adjustments to the technologies' returns after any particular path has been taken (Arthur 1989, p. 128). In Arthur's model, once the adoption process crosses either of the two absorbing barriers, the process is pushed further towards the outer regions and one of the two technologies

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11 These four properties have also been taken up by Pierson (2000). Sydow et al., however, criticize that the properties "seem to be somewhat overgeneralized" (Sydow et al. 2009, p. 691). Furthermore, they note that the four properties cover specific stages in a path-dependent process. On these grounds, the authors propose their phase model of path dependence as described in chapter 2.1.

12 Note that the property of unpredictability follows directly from the nonergodicity property of path-dependent processes (see section 2.1.3.3).

13 In other words, the final state of the process (i.e., a lock-in to a single technology) is predictable although the specific outcome (i.e., *which* of the competing technologies will win) is not. Referring back to the illustrative example of a plateau with drop-offs on both sides (see footnote 10), this means that the random walk will eventually fall off the plateau with certainty — however, it is unknown to which side.

drives the other out of the market. This behavior is termed ‘tipping’, which can be described as “the tendency of one system to pull away from its rivals in popularity once it has gained an initial edge” (Katz & Shapiro 1994, p. 106). In this end state, a marginal adjustment to the payoff structure no longer alters agents’ choices.

Arthur uses the term ‘lock-in’ to denote this state of inflexibility. Vergne & Durand (2010, p. 755) define lock-in as “a situation of relatively stable equilibrium caused by path dependence from which it is difficult to escape without the intervention of shocks exogenous to the system”. As Arthur’s model assumes *unbounded* increasing returns, the forces that would be required to ‘break the lock-in’ approach infinity in the long run. In this model environment, external shocks do not exist and the lock-in is irrevocable. In reality, however, Arthur’s assumption of unbounded increasing returns must be regarded as a very rare, extreme case. For most economic processes, increasing returns do not increase without limits. In this sense, nothing is forever: unforeseeable, strong external shocks can ultimately break a lock-in, and total inflexibility does not exist (Ackermann 2001, p. 20). Based on these considerations, lock-in must be conceived of as a *gradual* property instead of a binary concept. Markets become “becomes progressively more [or less] 'locked in'” (Arthur 1989, p. 117) and the ‘stability of lock-in’ can be measured by the magnitude of the external shock that is required to overcome the state of inflexibility.

2.1.3.3 Nonergodicity

A path-dependent process is *nonergodic* because several outcomes are possible and transient factors in the beginning of the process irreversibly determine which path will be taken. As Arthur (1989) notes, different sequences of historical small events lead to different outcomes. In his model, some choice sequences of the agents cause the market to tip in favor of technology A, while others result in a lock-in to technology B. As such, the small events early on in the process “cannot be treated … as ‘noise’”. Instead, “small events are remembered” (Pierson 2000, p. 253).

Formally, the concept of (non-)ergodicity can be expressed with reference to Markov chains (cf. Ross 1996).[14] A Markov chain is ergodic if any given state can be reached from any other state through a finite number of steps (Vergne & Durand 2010, p. 754). Accordingly,

[14] The intuitive Polya urn scheme is often applied to characterize nonergodic processes (Arthur et al. 1994; see also David 2007).

"stochastic processes that do not converge automatically to a fixed-point distribution of outcomes" are nonergodic (David 1985, p. 332).

Strictly speaking, nonergodicity is not a property but rather a necessary condition[15] for path dependence, generated by contingency and self-reinforcement. Both subconditions will be addressed in more detail in section 2.1.5.

2.1.3.4 Potential inefficiency

Lastly, a path-dependent process is *potentially inefficient* because the inherent process dynamics do not guarantee that the most efficient solution will be selected. Potential inefficiency is a consequence of the other properties of path-dependent processes: if several outcomes with different levels of efficiency are feasible given a set of initial conditions, and small events randomly determine which path will be chosen, then the emergence of an inefficient outcome is at least possible. Furthermore, given that a path-dependent process becomes inflexible and locks in, this inefficient outcome is also persistent. However, stressing the notion of *potential* inefficiency, it must be emphasized that inefficiency per se is not a necessary (nor sufficient) condition for path dependence (Ackermann 2001; David 2007).

Among the four properties, potential inefficiency plays a central role regarding the implications of path dependence theory. Taken together, the properties of unpredictability and inflexibility reveal that 'history matters'. Thus, path dependence constitutes a methodological counterpart to the "ahistorical nature of neoclassical theory" (David 1997, p. 12). In addition to this methodological implication, the claim of potential inefficiency also carries "normative implications" (Ackermann 2001, p. 20) for preventing or correcting inefficient, socially undesired outcomes provoked by path-dependent economic processes. Given its importance for path dependence theory, the inefficiency property and the resulting implications are discussed in more detail below.

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15 In this regard, Arthur is not very precise in his account of path-dependent processes (cf. Ackermann 2001, p. 19). Consistent with other narrow definitions of path dependence, for instance by Vergne & Durand (2010, p. 737), Arthur attributes path dependence to nonergodicity in the increasing returns case: "the process is non-ergodic or [i.e.] path-dependent" (Arthur 1989, p. 122). However, he later mixes properties and definitional criteria.

2.1.4 Debate on inefficiency and market failure

In general, the notion of inefficiency is used ambiguously in the literature on path dependence. Furthermore, the relationship between path dependence, inefficiency and market failure often remains unclear. Much of the criticism directed towards path dependence theory, most prominently by Liebowitz & Margolis (1990, 1995), originates from a misinterpretation of the connection between path dependence and market failure. Therefore, a clarification of this critical issue is necessary.

In his early account on the QWERTY standard, David (1985, p. 332) emphasizes the increased efficiency (in a technical sense) that would have been obtained with the superior Dvorak keyboard. According to him, QWERTY's dominance is a prime example for "standardization on the wrong system" (David 1985, p. 336). Although this clearly implies that the outcome is unsatisfactory and undesirable from a macro perspective, the author avoids the term 'inefficient' in his original paper (David 1985).[16] However, he describes the situation to be "Pareto-inefficient" in a later paper (David 2007, p. 91). The Pareto criterion is the standard efficiency argument in microeconomics. Pareto inefficiency implies that the utility of at least one person could be improved without making anyone worse off, allowing that prospective gainers could compensate prospective losers. In this regard, the QWERTY standard is considered as inefficient because we would collectively be better off if a different path (towards a superior keyboard standard) had been taken early on.[17]

Arthur's model on competing technologies (Arthur 1989) applies the notion of inefficiency in a very different manner. In this model, neither of the two technologies is defined to be superior or inferior to the other.[18] Instead, the two types of agents have a natural preference

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16 Nevertheless, David used the notion of inefficiency to capture the audience's attention for his first talk on the QWERTY case at the *American Economic Association* meeting in 1984 (David 1997, pp. 8-10).

17 I will discuss this argument in more detail in section 2.1.4.3, highlighting the role of individual/collective costs and benefits, as well as the resulting implications for path dependence theory.

18 Note that in addition to the described model, the seminal paper of Arthur (1989) includes a "trivial example" (Arthur 1989, p. 119) where a market becomes locked-in to a technology that is inferior in the long run. In this case, the outcome is clearly inefficient. However, Arthur admits that the model behavior is trivially predictable: all agents choose the same technology, there are no random events and the process lacks the property of nonergodicity. Consequently,

for one of the two technologies. Arthur argues that if the market locks in to one of the technologies, the group of agents that initially favored the other technology will 'regret' the outcome. This 'regret' criterion is Arthur's conceptualization of path-inefficiency (Arthur 1989, p. 119). However, this criterion has several drawbacks. Following Arthur's approach, every allocation that deviates from a 50:50 distribution (in which both groups of agents adopt the technology they initially preferred) is considered as inefficient. Such a conceptualization is quite counterintuitive. From a Pareto perspective, in contrast, one would need to compare the losses of the group that regrets the outcome with the gains of the other group that benefits from greater adoption of their preferred technology. Furthermore, Arthur's approach ignores the effect of the increasing returns parameters r and s in the model. For large values of r and s, both types of agents will prefer a dominance of either technology to a 50:50 split. In these cases, a lock-in to either of the two technologies is 'efficient', both from an individual and collective perspective.

To conclude, the property of inefficiency is ambiguously used in the path dependence literature, even by its most prominent contributors.

2.1.4.1 Critique by Liebowitz and Margolis

Since the very beginning, the claim of potential inefficiency has been the apple of discord and has brought path dependence theory strong criticism from some scholars. Most prominently, Liebowitz & Margolis (1990, 1995) contest the concept of path dependence by opposing the inherent inefficiency argument. In a response to David's original paper (David 1985), Liebowitz & Margolis accuse David's historical account of the QWERTY case of not reporting the "true history" (Liebowitz & Margolis 1990, p. 2). Furthermore, they deny the empirical evidence of QWERTY's inferiority. The authors raise methodological concerns about the U.S. Navy study that found the Dvorak keyboard to be more efficient than QWERTY. In addition, they give reference to ergonomic studies which suggest that the advantage of the Dvorak keyboard is at best marginal. Taken as a whole, however, Liebowitz & Margolis' arguments are not convincing. Even they must admit that the QWERTY keyboard may not be "the fittest that can be imagined" (Liebowitz & Margolis 1990, p. 8), and despite their fierce criticism, QWERTY is still widely

the trivial example should not be regarded as a model of technological path dependence. See also Liebowitz & Margolis (1995, pp. 214ff.), who discuss the inconsistency of this example.

perceived as being a clearly inferior standard (Shapiro & Varian 1999; Rogers 2003; Farrell & Klemperer 2007, among others).

Apart from their empirical objections against the QWERTY case, Liebowitz & Margolis have raised further concerns about the validity of path dependence theory. Much of their criticism centers around the property of potential inefficiency and the (false) understanding that path dependence causes market failure. Serving as basis for argumentation, Liebowitz & Margolis (1995, pp. 206-209) discuss three possible efficiency outcomes of a path-dependent process and thereby distinguish among three different degrees of path dependence.

First-degree path dependence refers to dynamic processes that are sensitive to initial decisions. However, this form of path dependence holds that the long-term effects on efficiency have either been fully taken into account by the decision-maker (assuming perfect information), or that the outcome has no implied inefficiency at all. Liebowitz & Margolis provide a fairly trivial example for illustration: first-degree path dependence arises when one decides to part one's hair on the left or right. This initial decision is likely to persist over a lifetime, but neither direction is considered to be inefficient in any meaningful sense (Liebowitz & Margolis 1995, p. 206-207). For economic theory, first-degree path dependence is of little interest and has no normative implications (Ackermann 2001).

Second-degree path dependence relates to cases with imperfect foresight. In this form, the decision that triggered a certain path was efficient because it reflected all available information at the time the choice was made. However, the outcome of the path-dependent process may appear inefficient *in retrospect* when new information is discovered or new choice alternatives arise. For instance, a chosen technology may turn out to be inferior to another that has recently become available due to technological progress. Such outcomes are "regrettable and costly to change" (Liebowitz & Margolis 1990, p. 8). However, the authors conclude that second-degree path dependence is "not inefficient in any meaningful sense, given the assumed limitations of knowledge" (Liebowitz & Margolis 1995, p. 207). This view is supported by Williamson (1993), who argues that an allocation is only inefficient in a strict sense if it is remediable, which means that the optimal solution could have been achieved.

Third-degree path dependence occurs when "there exists or existed some feasible arrangement for recognizing and achieving a preferred outcome, but that outcome is not obtained" (Liebowitz & Margolis 1995, p. 207). In other words, the outcome of the path-dependent process constitutes a *remediable* inefficient state. For instance, third-degree path dependence describes cases where the market locks in to an inferior technology even though a superior alternative was already available at the time the path was embarked upon. In this case, the outcome is inefficient *ex-ante,* in that the inferiority of the chosen path should have been known (Ackermann 2001). This third-degree path dependence is the strongest form of path dependence and the only one that has caused turmoil with advocates of the neoclassical paradigm of efficient decentralized markets.

2.1.4.2 Different degrees of lock-in

Although proposed with different intentions, Liebowitz & Margolis' (1995) distinction among different efficiency outcomes is believed to be of value to the path dependence literature. It highlights the difference between inefficiency ex-ante and inefficiency ex-post[19], thus raising awareness for the temporal perspective that needs to be taken into account when assessing (in)efficiency. However, the authors overemphasize the efficiency property within path dependence theory and incorrectly restrict the notion of 'lock-in' to cases of third-degree path dependence (Ackermann 2001; David 1997).[20] In fact, the efficiency considerations suggested by Liebowitz & Margolis do not apply to the process itself (i.e., the emergence of the path), but solely relate to the final lock-in state. Rather than referring to three 'degrees of path dependence', a more suitable terminology is to differentiate between three 'degrees of lock-in'. This terminology better emphasizes that path dependence should not be reduced to efficiency considerations. Instead, the distinction serves to describe the nature and severity of lock-ins more closely by drawing on well-established efficiency classifications.

In the technology context, a first-degree lock-in refers to the dominance of a single technology that is not inferior to other possible alternatives, i.e., either the optimal outcome has been achieved or all outcomes are equally efficient. In contrast, both second- and third-degree lock-ins designate the dominance of a technically inferior technology. Corresponding to Liebowitz & Margolis conceptualization, the remediability condition distinguishes second-degree from third-degree lock-ins. A second-degree lock-in describes the dominance of a single technology that is suboptimal *in retrospect* because better alternatives have since become

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19 See also Farrell & Klemperer (2007, pp. 2012-2013).

20 Instead of focusing on efficiency considerations, David rightly argues for characterizing path-dependent processes by their "degree of historicity" (David 1997, p. 27).

available, for instance due to technological progress. A third-degree lock-in occurs when an inferior technology dominates the market even though a superior standard could have been obtained: a third-degree lock-in is remediable and thus inefficient. Remediability manifests itself not only by reference to the temporal order in which a superior alternative became available; a lock-in is also regarded as remediable when the collective benefits from switching to a superior alternative exceed the collective switching costs.[21] This cost-benefit analysis will be of particular importance for the normative implications of path dependence theory.

2.1.4.3 Path dependence and market failure

The discussion of the different degrees of lock-in leads us to the questionable association of path dependence with market failure. David complains that path dependence "has been denounced as harboring the contention that 'markets fail'" (David 2007, p. 102).[22] This misunderstanding must be largely attributed to the works by Liebowitz & Margolis (1990, 1995). They argue that the QWERTY case is positioned as an example of third-degree path dependence and claim that "third-degree path dependence is a dynamic market failure" (Liebowitz & Margolis 1995, p. 209). However, neither David (1985) nor Arthur (1989) mention the term 'market failure' in their seminal papers. In a response to Liebowitz & Margolis, David makes clear that "the concept [of path dependence] itself carries no necessary implications whatsoever in regard to the existence or non-existence of 'market failure'" (David 2007, p. 103) and that "the logical relationship between path dependence and market failure is neither one of necessity nor sufficiency" (David 2007, p. 104). Nevertheless, there are arguably some connections between path dependence and market failure, though the relationship is not causal. Therefore, it is necessary to disentangle the argumentative confusion that has fueled the conflict between proponents and opponents of path dependence theory.

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21 Although Liebowitz & Margolis do not refer to a cost-benefit analysis of switching in their definition of the different degrees, they later note: "if it were widely understood today that switching to Beta has a benefit greater than the cost, but we remain mired in the VHS standard, we would have another instance of third-degree path dependence" (Liebowitz & Margolis 1995, p. 209).

22 Throughout this thesis, market failure is understood as violation of the "Pareto optimality of allocations yielded by … atomistic, competitive markets" (David 2007, p. 103).

In brief, path dependence creates the *potential* for market failure. However, the market failure itself is to be attributed to market imperfections instead of being caused by path dependence. In order to fully grasp this controversial, often misunderstood issue, one needs to acknowledge the presumptions of both parties (cf. Lewin 2001).

Assuming the perfect world of neoclassical economics, Liebowitz & Margolis (1990, 1995) start from the basic premise that an inefficient market outcome is, at most, a short-lived phenomenon. The authors argue that cases of third-degree lock-in imply profit-making opportunities for rational agents that are able to exploit some of the benefits to society of switching to a superior standard. As such, they conclude that "the greater the gap in performance between two standards, the greater are these profit opportunities, and the more likely that a move to the efficient standard will take place" (Liebowitz & Margolis 1990, p. 4). To summarize, their argument asserts that market forces will eliminate sources of substantial inefficiency.

David acknowledges that the idea of profit-seekers who find ways to benefit from rectifying inefficiencies "undoubtedly warrants serious consideration in this regard"[23], however it "ought not be accepted on faith" (David 2007, p. 106). The line of reasoning from Liebowitz & Margolis (1990, 1995) as well as the response by David (1997, 2007) are best illustrated by referring back to the keyboard example. In the following section, I first discuss whether the emblematic case of QWERTY constitutes a market failure. Then, assuming for the moment that it is a market failure, I elaborate on what has caused the market to fail. As will be shown, the claim that path dependence implies market failure is not acceptable.

Does QWERTY's dominance constitute a market failure?

Let us assume that Dvorak is indeed superior to the QWERTY keyboard layout to some degree. Liebowitz & Margolis rightly argue that market failure requires the existence of a persistent third-degree lock-in, which is or would have been remediable. Remediability manifests itself as one of two conditions. First, remediability holds in cases where the market locks in to an inferior technology even though a superior alternative was already available at the time the sub-optimal

[23] In fact, David agrees with Liebowitz & Margolis that "the self-interest of actors may be engaged to seize the opportunities it affords them to benefit by offering a more satisfactory solution" (David 2007, p. 105).

path was embarked upon ('order-of-entry argument'). Second, a lock-in is deemed remediable if the benefits of switching to a superior technology outweigh the costs ('cost-benefit argument').

Given that Dvorak was patented in 1936 (Liebowitz & Margolis 1990), some 60 years after the first QWERTY typewriter models were sold, the order-of-entry argument does not apply. As such, the only way to claim market failure would be to argue that the collective benefits from adopting Dvorak would outweigh the collective switching costs ('cost-benefit argument'). Collective benefits to society include the higher productivity achieved from faster typing as well as one-time gains from faster learning when new users train directly on Dvorak. Collective benefits are the sum of the individual benefits, including the benefits for future generations. On the opposite side, collective switching costs include the physical replacement of QWERTY keyboards as well as the time and effort to retrain people on Dvorak. For proponents of efficient markets who deny that the QWERTY lock-in is remediable, it is crucial to show that the potential benefits from switching to an alternative keyboard layout would not outweigh the costs of switching. This is why they fiercely contest the inferiority of the QWERTY standard and downplay the benefits of Dvorak, e.g.: "the advantages of the Dvorak is either small or nonexistent" (Liebowitz & Margolis 1990, p. 15). Given that both collective benefits and collective switching costs are difficult to quantify, neither market failure nor the opposite can be proved with certainty. Even if one concludes that Dvorak is not sufficiently superior to outweigh the collective costs for switching, the cost-benefit analysis may change when including the benefits for future generations.[24] Here, the time horizon is crucial: would the benefits of moving to Dvorak accrue for numerous future generations, or will any physical keyboard be replaced by speech recognition or some other disruptive technology in a few years' time? Only time will tell and any claim is mere speculation.

If there is market failure, what has caused markets to fail?

Given that market failure in the QWERTY case cannot be proved with certainty, let us assume for the moment that there is market failure. In this case, the collective benefits from switching outweigh the collective switching costs, so a transition would be worthwhile from a societal viewpoint. What, then, are the reasons for QWERTY's continued dominance? It is important

[24] In this thought experiment, future generations would train directly on the superior Dvorak keyboard. Thus, they would benefit from higher productivity without incurring switching costs.

here to distinguish between individual and collective costs and benefits. Individual switching costs include the costs for replacement and retraining *plus* the loss of compatibility with the QWERTY-dominated environment. For instance, when learning Dvorak on a private computer at home, typing on a QWERTY keyboard at work will become very difficult. Furthermore, the selection of Dvorak hardware (keyboards, or laptops with integrated keyboards) is extremely limited compared to the dominant QWERTY standard. As a result, even though switching to Dvorak may be beneficial for society as a whole, the individual switching costs may still exceed the individual benefits. In other words, technical interrelatedness, or the 'indirect network effect', hinders the switch to the superior technology. For an individual, leading the move to Dvorak is not rational given that compatibility is lost with the prevalent QWERTY hardware. Hence, there is a conflict between individual and collective rationality.

Liebowitz & Margolis (1990, pp. 4-5) argue that in such cases a profit-seeking entrepreneur will internalize the switching cost, for instance by discounting Dvorak keyboards, offering guarantees of its superiority or even providing free training classes. In return, the profit-seeker will reap some of the benefits that are gained when switching collectively to Dvorak, for instance by receiving patent royalties for Dvorak. According to this view, an inefficient market outcome is, at most, a short-lived phenomenon. Sooner or later, market forces will eliminate the sources of market failure and guide society on the efficient path.

Assuming that QWERTY constitutes an inefficient outcome, why has no one successfully challenged its more than one-hundred-year dominance? In other words, who is to blame for the market failure? The sources of market failure are well known to economists and have no exclusive, causal link to path dependence theory: market imperfections that, for instance, lead to coordination failure. Coordination failure occurs under the condition of "information imperfections that make it unlikely that a decentralized process can get everyone coordinated to move elsewhere, collectively" (David 1997, p. 35). Referring back to the QWERTY example, a global move to Dvorak would pose serious coordination problems that deter any profit-seeking entrepreneur from undertaking such a venture. Market failure due to coordination problems has been intensively studied by game theorists since the 1950s, for instance in the context of the Prisoner's dilemma.[25] Apart from coordination problems, in other

[25] The Prisoner's dilemma was conceptualized by Merrill Flood and Melvin Dresher at the RAND corporation in the 1950s. It was then formalized by Albert W. Tucker, who also gave it its name.

cases 'markets' may not exist due to poorly defined property rights, and profit-seekers are therefore unable to reap the benefits from a coordinated switch towards a superior alternative (Liebowitz & Margolis 1995). In both scenarios, market imperfections prevent a coordinated escape from a third-degree lock-in. Lastly, real-world economic actors deviate from the purely theoretical construct of a 'homo oeconomicus'. As such, incomplete information, bounded rationality and limited reaction capabilities may prevent economic actors from identifying and choosing the optimal technology. In this context, path dependence theory highlights the negative side of interdependent actions, where an "individual actor becomes entrapped in the system's dynamics" (Sydow et al. 2009, p. 691). In all cases, inefficient third-degree lock-ins can possibly persist.

In summary, the notion of path-inefficiency is used in various different ways throughout the path dependence literature. The proposed distinction between three degrees of lock-in is helpful to differentiate among different efficiency outcomes. A third-degree lock-in occurs when a path-dependent process results in a Pareto-inefficient outcome even though better alternatives are feasible, meaning that the outcome is remediable in principle. Even when switching is worthwhile from a societal viewpoint, a conflict between individual and collective rationality can prevent the smooth transition to a superior technology. Table 2-2 shows the possible results of an individual and collective cost-benefit analysis and summarizes the implications.

Table 2-2 **Cost-benefit analysis of switching to a superior technology**

Individual benefits:	e.g., higher productivity
Individual switching costs:	e.g., replacement, retraining, loss of compatibility
Collective benefits:	sum of individual benefits, including future generations
Collective switching costs:	sum of individual costs, but without loss of compatibility

		Individual benefits > individual switching costs	
		Yes	*No*
Collective benefits > collective switching costs	*Yes*	People will switch to the superior technology on their own -> no lock-in	Outcome is remediable, but a coordinated escape is needed. Lock-in may persist because of market imperfections. -> 3rd degree lock-in, creates the *potential* for market failure due to market imperfections
	No	Not applicable here (no negative externalities).	Not inefficient in a strict sense (assuming that the superior technology became available afterwards) -> 2nd degree lock-in

A third-degree lock-in is the only type that is associated with market failure. In general, it is assumed that market forces will guide society onto the efficient path by offering profit opportunities to entrepreneurs who find ways to benefit from rectifying inefficiencies. However, market imperfections may prevent a coordinated escape from a third-degree lock-in, causing a socially inefficient outcome to persist.

Credit must be given to path dependence theory for drawing attention to this particular type of process where violations of standard neoclassical assumptions have especially problematic long-term consequences. Nonetheless, the root causes of market failure, i.e., various forms of market imperfections, are not exclusively related to path dependence theory itself. Put differently, the dynamics of path-dependent economic processes carry the *potential* for market failure — however, the market failure itself is to be attributed to market imperfections, such as coordination problems and boundedly rational actors. Therefore, there is no direct causal link between path dependence and market failure.

2.1.5 Conditions for path dependence

After having enlightened the controversy over market failure, I now elaborate on the necessary conditions for path dependence. It has already been argued that a narrow understanding of technological path dependence that goes well beyond the metaphorical notion of 'history matters' is required to unleash the full potential of the construct. In this regard, nonergodicity is the crucial element that characterizes path-dependent processes (David 1985; Arthur 1989; Ackermann 2001).[26] A process is nonergodic when different outcomes are possible and contingent events trigger self-reinforcing dynamics that irreversibly determine which path will be taken. Following this understanding, nonergodicity occurs under the *joint conditions* of contingency and self-reinforcement. In line with this argument, path dependence is defined as the "property of a stochastic process which obtains under two conditions (contingency and self-reinforcement) and causes lock-in[27] in the absence of exogenous shock" (Vergne & Durand 2010, p. 737). Drawing on this definition, both contingency and self-reinforcement are necessary conditions that distinguish path dependence from other related concepts. I elaborate on these two necessary conditions below.

2.1.5.1 Contingency

According to Luhmann, contingency means excluding necessity and impossibility: "something is contingent insofar as it is neither necessary nor impossible" (Luhmann 1995, p. 106). As such, contingency is associated with open, non-deterministic processes where many directions are feasible. Excluding necessity and impossibility implies that the outcome is, at least partly, random and not strictly caused by structural forces. Consequently, contingency is characterized by "unpredictable, non-purposive, and seemingly random events" (Vergne & Durand 2010, p. 755). Applying this concept, an event is said to be 'contingent' if it can occur or not occur — both alternatives are possible.

26 Nonergodicity has also been discussed in section 2.1.3.3.

27 'Lock-in' is understood as "a situation of relatively stable equilibrium, caused by path dependence, from which it is difficult to escape without the intervention of shocks exogenous to the system" (Vergne & Durand 2010, p. 755). As such, the notion of lock-in alone has no implied claim of inefficiency. In this respect, the proposed distinction between first-, second- and third-degree lock-ins allows us to further distinguish between different efficiency outcomes.

At the beginning of a path-dependent process, contingent events can have significant long-term consequences. Contingent, or random, events are called ‘small events’ if they unintentionally steer the process in a specific direction, triggering positive feedback mechanisms that reinforce the selected path. As a result, the contingent process becomes increasingly deterministic as the self-reinforcing dynamics unfold.

Although the notion of ‘small events’ is deeply rooted in path dependence theory, the concept lacks a clear definition. Originally, David vaguely referred to “temporarily remote events” that exert “important influences upon the eventual outcome” (David 1985, p. 332), but he neither explicitly labels them as ‘small events’ nor provides a concise definition. The first author to explicate the concept of small events is Arthur (1983, 1989). He defines “historical small events” as “events or conditions that are outside the ex-ante knowledge of the observer — beyond the resolving power of his 'model' or abstraction of the situation” (Arthur 1989, p. 118). This definition clearly distinguishes small events, which occur randomly and are thus unpredictable, from initial conditions, which are known ex-ante.[28]

2.1.5.2 Self-reinforcement

In combination with contingency, self-reinforcement is the second necessary condition of path-dependent processes. In the context of path dependence theory, self-reinforcement is a general term for the effect whereby “the increase of a particular variable leads to a further increase of this very variable” (Sydow et al. 2009, p. 694). Self-reinforcing mechanisms[29] are at the heart of understanding technological paths, which emerge due to the interdependent choices of economic actors in a decentralized market setting. Arthur (1989) stresses the notion of ‘increasing returns’ to describe how a decision by one actor in favor of a certain technology directly or indirectly increases its attractiveness (in terms of pay-off / utility) for other actors. The resulting self-reinforcing dynamics ultimately enforce the dominance of a single technology, thereby forming a ‘path’ of interrelated decisions. Drawing on Arthur (1994, p. 112), I elaborate

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28 See also Mahoney (2000), who discusses in detail the role of initial conditions in path-dependent processes.

29 In line with prior literature on path dependence, the terms ‘self-reinforcing mechanisms‘ and ‘positive feedback mechanisms’ are used interchangeably. Vergne & Durand describe these as a “set of mechanisms endogenous to a given path that makes it more and more dominant over time relative to alternative paths” (Vergne & Durand 2010, p. 755).

on four different types of self-reinforcing mechanisms that are typically mentioned in the context of competing technologies: (1) supply-side economies of scale, (2) learning effects, (3) adaptive expectations and (4) network effects.

2.1.5.2.1 Supply-side economies of scale

Supply-side economics of scale describe the inverse relationship between production output and unit cost. Supply-side economies of scale can take different forms (cf. Pindyck & Rubinfeld 2005, pp. 225-239). First, set-up or fixed costs are distributed over more product units when output increases. As a result, the fixed costs per unit decrease. This effect is termed 'fixed-cost-degression'. Second, higher production volumes allow for lower procurement costs. As a result, the variable costs per unit decrease. Third, learning effects in production bring about higher productivity and lower scrap rates, also leading to lower unit costs.[30]

To conclude, supply-side economies of scale reduce production cost as the scale of output is increased. If for some reason[31] one technology has a small (and even transitory) advantage over its competitors, the higher sales of that technology lead to higher output levels and thus lower unit costs compared to its competitors. Because of this cost advantage, the technology becomes cheaper and thus more attractive for consumers, which further increases its market share.[32] These dynamics highlight the self-reinforcing nature of supply-side economies of scale.

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30 In contrast to the first two forms of supply-side economies of scale, this third effect refers to the *cumulative* output level over time. This 'learning curve effect' is rooted in psychology and was supported in academic studies already in the late 19th century by Edward Thorndike and others (cf. Argote et al. 1990). At the industrial level, it was systematically explored in empirical studies by the *Boston Consulting Group* in the 1960s, and has since then become a popular tool for business strategy (Lieberman 1987).

31 One common reason for an early lead in adoption is being first to market. However, a first-mover advantage is typically not a contingent event, but instead determined by the initial conditions of the process. In this context, Vergne & Durand (2010) argue that, from a strict understanding, a technological lock-in due to a first-mover advantage does not qualify as a path dependence explanation.

32 In addition, higher unit sales provide the necessary financial means for investments in quality improvements and product development (given that one assumes limited financial resources for less successful firms).

2.1.5.2.2 Learning effects in consumption

In addition to supply-side learning effects in production, learning effects also appear on the consumer side. Referred to as 'learning-by-doing', users benefit from the experience they gain while using a certain technology. Over time, consumers gain practice with the technology and learn to employ it in a more efficient way. Due to these learning effects, consumers develop a strong preference for their chosen technology, which thereby becomes more attractive relative to alternative technologies. As a result, consumers are less likely to switch, and inflexibility at the individual level occurs. Referring back to the keyboard example, users' touch-typing skills on QWERTY quickly improve over time as they memorize the particular key arrangement and thus improve their efficiency. Because users would need to invest considerable time and effort to retrain on an alternative keyboard layout, learning effects in favor of QWERTY result in the 'quasi-irreversibility' of their initial keyboard choice.

Although learning effects in consumption and the resulting individual inflexibilities on the consumer side can partly explain the *maintenance* of a path, they cannot explain the *emergence* of a path (Ackermann 2001). Technological path dependence in a decentralized market setting requires that economic actors *independently* choose the *same* technology. However, individual learning effects do not establish this coordination between the decisions of different actors. In other words, learning effects may well explain why consumers stick to their individual technology choice, but they cannot account for the move towards a common standard. In the context of the keyboard example, individual learning effects dissuade users from switching to the Dvorak keyboard, but they do not explain why QWERTY was commonly chosen in the first place (Ackermann 2001). At this point, researchers must draw upon alternative explanations for the early prevalence of the QWERTY standard.[33] To conclude, learning effects explain individual inflexibilities but should not be conceived as a self-reinforcing mechanism at the market level.

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[33] As discussed in chapter 2.1.1, the technical interrelatedness between the keyboard layout and the touch-typing skills of typists was particularly responsible for QWERTY's dominance. This relation is also known as an indirect network effect, which will be addressed in the following section.

2.1.5.2.3 Adaptive expectations

Adaptive expectations are another important mechanism that is frequently brought forward to explain technological lock-ins. The role of expectations is already highlighted in the seminal works by David (1985) and Arthur (1989). David argues that the outcome of a technology battle is not simply determined by a comparison of the current costs and benefits of the different systems, but instead strongly influenced by expectations of future developments: "a particular system could triumph over rivals merely because the purchasers of the software (and/or the hardware) expected that it would do so" (David 1985, p. 335). This effect plays a critical role when technologies serve as standards.[34] In this case, agents' benefit of using a particular technology depends on the past and future choices of other agents. The expected utility of a technology increases if it is believed that other agents will choose the same technology. Ultimately, if economic actors *assume* that the market will end up in a lock-in to a certain technology, their expectations will actually enforce the lock-in. In this regard, adaptive expectations act as a self-fulfilling prophecy: higher prevalence of any particular technology enhances belief in its continued prevalence, resulting in the actual dominance of this technology. Referring back to Arthur's original model (see section 2.1.2), "expectations of lock-in hasten lock-in, narrowing the absorption barriers and worsening the fundamental market instability" (Arthur 1989, p. 123).

Although their important role for technological path dependence has to be acknowledged, adaptive expectations should not be regarded as an autonomous source of positive feedback dynamics. Instead, adaptive expectations intensify and reinforce other positive feedback mechanisms (Ackermann 2001). The expected prevalence of a particular technology influences agents' choices only if it is individually beneficial to choose the prevalent technology. Therefore, adaptive expectations are only effective if there is *some other* increasing returns mechanism that provides an incentive to choose a widely adopted technology (Ackermann 2001). In short, economic agents decide for the expected standard not because they care about the expectations *per se*, but rather because choosing the prospective standard is of value to them — which is the true source of increasing returns to adoption.

[34] For a good introduction to technological standards, including a discussion of the different methods for standard-setting, refer to Axelrod (1997, pp. 96-102).

In conclusion, adaptive expectations are not an autonomous mechanism for technological path dependence, but instead reinforce other positive feedback mechanisms. In particular, Katz & Shapiro highlight the importance of consumers' expectations in markets with network effects (Katz & Shapiro 1985). Against this background, the following section discusses the vital role of direct and indirect network effects for the formation of technological lock-ins.

2.1.5.2.4 Network effects

Network effects occur when the value of a technology depends on the number of other adopters. In most cases network effects are positive, which means that a technology becomes more valuable as it is used more widely (Shy 2011).[35] The concept is described in the literature under various different names, such as 'network externalities'[36] or 'demand-side economies of scale'. In contrast to supply-side economies of scale, which generate cost advantages in production due to higher adoption, demand-side economies of scale occur in the usage, or consumption, of the technology. For this reason, Katz & Shapiro use the term 'consumption externalities', referring to the effect whereby "the utility that a user derives from consumption of the good increases with the number of other agents consuming the good" (Katz & Shapiro 1985, p. 424).

The notion of network effects dates back to the early works by Leibenstein (1950), Rohlfs (1974) and the seminal paper by Katz & Shapiro (1985). Network effects have become increasingly important in recent years, as the "information economy is driven by economies of networks" (Shapiro & Varian 1999, p. 173). In the last twenty-five years, a vast body of literature

[35] Negative network effects may arise due to congestion and interference, as well as due to "snobbism or vanity, in that a consumer loses the sense of belonging to an elite group when a product is adopted more widely" (Shy 2011, p. 120). However, these are very special cases and the overwhelming majority of the literature focuses on positive network effects (Liebowitz & Margolis 1994).

[36] This terminology highlights that new adopters of a technology create a positive externality by increasing the utility of the existing adopters. However, economic agents do not consider this positive side effect on third parties in their choice of technology. The term 'externality' generally carries a negative connotation in the field of economics, and implies that there is some potential for sub-optimal market outcomes (Liebowitz & Margolis 1994). For instance, network externalities may result in under-adoption of the technology (Farrell & Klemperer 2007, pp. 2016-2020). On that account, Liebowitz & Margolis (1994) suggest reserving the term 'network externality' for a "specific kind of network effect in which the equilibrium exhibits unexploited gains from trade regarding network participation" (Liebowitz & Margolis 1994, p. 135).

on this topic has accumulated in the domains of industrial economics, strategy and marketing. A full literature review would go beyond the scope of this introduction, which concentrates only on the foundational contributions.[37]

Network effects can be divided into 'direct effects' and 'indirect effects' (Katz & Shapiro 1985). Direct network effects occur when the number of network participants directly influences a product's utility (Rohlfs 1974). In such cases, the total value of the network to any participant depends on the number of connected compatible nodes. This effect can be most notably seen in communication networks, the classic example being the telephone network. Being the only telephone user on earth does not yield much benefit. However with rising adoption of the technology, the number of subscribers that can be reached by phone grows. As a result, the value of the telephone network increases for existing as well as potential users (Church & Gandal 1993). In this case, users directly benefit from a larger network size. Modern examples for the presence of direct network effects include online communities such as *Facebook* or *LinkedIn*, as well as peer-to-peer communication services such as *Skype*, where the utility for each participant depends on the number of other people that can be contacted.

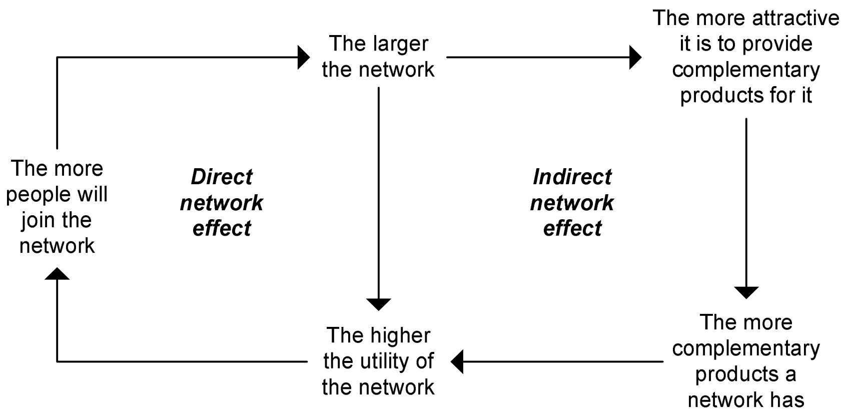
Indirect network effects occur when the utility of a technology depends on complementary goods and services provided by independent firms. For instance, to be of value, PCs require software and DVD players require prerecorded DVDs. Such systems of complements are described by the "hardware/software paradigm" (Katz & Shapiro 1985). Consumers *indirectly* benefit from a higher adoption of the technology by other consumers as it improves the availability of complementary products, which in turn enhances the value of the technology. A common example is PCs and their operating systems: widespread adoption of any particular system (e.g., *Windows*, *Mac* or *Linux*) encourages "further software developers and

37 Several overview articles offer suitable entry points into the literature: Shy (2011) provides a recent survey of network effects in the economic literature. Koski & Kretschmer (2004) review the literature on market structure and firm strategies in network industries. In a similar way, McIntyre & Subramaniam (2009) evaluate theoretical and empirical contributions on the implications of network effects for strategic management. Birke (2009) categorizes 38 empirical studies on network effects between 1992 and 2007 and summarizes their methodological approaches as well as their main findings. A well-written (German) round-up is provided by Clement & Schollmeyer (2009).

hardware manufacturers to adopt it, which helps it get further ahead" (Arthur 1996, p. 102).[38] Hardware/software systems can be conceived of as "virtual networks that give rise to feedback effects similar to those associated with physical networks" (Katz & Shapiro 2004, pp. 1-2). Expanding the concept beyond physical networks, the term 'network' more generally refers to a group of users ('network participants') who use the same or a compatible technology (Shy 2011). Similar to complementary goods, the utility of a technological product is often influenced by the availability of complementary post-purchase services or the existence of a technical infrastructure, which also gives rise to positive indirect network effects (Katz & Shapiro 1985). For instance, the benefit from an electrically powered car depends on the number of compatible charging stations.

Figure 2-3 summarizes the interplay between direct and indirect network effects and highlights their self-reinforcing nature.

Figure 2-3 **Direct and indirect network effects**
(Source: Adapted from Koch et al. 2009, p. 69)



To conclude, network effects are a prime example of positive feedback processes in which "success begets more success" (Shapiro & Varian 1999, p. 174). If a particular technology takes a contingent lead in adoption, direct or indirect network effects further increase the attractiveness

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38 To be precise, the operating system software (instead of the PC itself) takes on the role of the 'hardware' and software applications take on the role of 'software'. Hence, this most frequent example of the hardware/software paradigm is semantically confusing (Farrell & Klemperer 2007, p. 2008). The relationship between PCs, operating systems and complementary software applications will receive further attention in the discussion on software platforms (please refer to section 2.2.1).

of the technology in comparison to others, and the selected path becomes increasingly dominant. Likewise, the same dynamics enforce that "failure breeds failure" (Shapiro & Varian 1999, p. 174): when participants leave the network, they create an incentive for the remaining participants to leave as well. Consequently, network effects drive a virtuous cycle for the most widespread technology and a vicious circle for its competitors, and thus tend to produce extreme market outcomes.

Having described the various self-reinforcing mechanisms that give rise to technological lock-ins, I now devote particular attention to self-reinforcement by means of indirect network effects. The following section addresses the related concept of two-sided markets, which provides deeper insight into the economics of network markets in general and the role of indirect network effects in particular. As will be shown, two-sided markets offer a rich field of study from a path dependence perspective.

2.2 Two-sided markets: A holistic perspective on indirect network effects

The understanding of indirect network effects has been enhanced by the theory of two-sided markets (Rochet & Tirole 2003; Parker & Van Alstyne 2005; Rochet & Tirole 2006; Armstrong 2006).[39] This concept provides an actor-centric view on the origin and impact of indirect network effects. One can think of two-sided markets as a holistic perspective on indirect network effects that highlights the interdependence of the decisions of two sets of agents as well as their interactions (Sundararajan 2006).[40]

In a two-sided market, "two sets of agents interact through an intermediary or platform, and the decisions of each set of agents affects the outcomes of the other set of agents, typically through an externality (in usage or membership)" (Rysman 2009, p. 125). The notion of two-sided markets emphasizes that indirect network effects are typically two-sided: the utility of one group's members depends on the size of the other group *and vice versa* (Armstrong 2006; Rochet & Tirole 2006).[41] Furthermore, in order to mutually provide each other with indirect network effects, both groups of actors require some form of intermediary, termed a 'platform'.

I have already addressed the example of operating systems and compatible software applications to illustrate indirect network effects. Applying the notion of two-sided markets, the operating system can be thought of as a software platform that brings together computer users

39 In accordance with the majority of the literature, I use the term 'two-sided market' although many markets are in fact multi-sided, consisting of three or more sides. However, the insights obtained for two-sided markets can be generalized to multi-sided markets (Rochet & Tirole 2006). Some scholars prefer the term 'platform market' (Gawer 2009, p. 124, see footnote 4). Others use the term 'two-sided platform' or 'multi-sided platform' (MSP) when referring to the market as a whole (Evans & Schmalensee 2008). All of these terms describe the same class of phenomena and are used synonymously in the literature (Evans & Schmalensee 2008, p. 667).

40 To put it differently, indirect network effects are often a one-directional perspective on two-sided markets (Sundararajan 2006).

41 Therefore, indirect network effects are also termed cross-side network effects (Economides & Katsamakas 2006). Note that cross-side network effects can be positive in one direction and negative in the other, for instance when advertisers seek a large audience, but consumers dislike advertising. Analogously, direct network effects can be regarded as same-side network effects (Rochet & Tirole 2003): increasing the number of users on one side of the platform makes participation more (or sometimes less) beneficial to users on the same side (Eisenmann et al. 2006).

and third-party software developers.[42] Computer users benefit from a large group of software developers which provide compatible applications for their PCs. From the other perspective, developers benefit from a large group of users, which makes the provision of software applications for that platform more attractive. This interdependence highlights the two-sided nature of the indirect network effects. For software platforms, the operating system forms the interface between consumers' computer hardware and compatible software applications by providing standard components, and thus acts as an intermediary between computer users and software developers. In order to establish a successful software platform, the provider of the operating system needs to get both sides "on board" (Rochet & Tirole 2006).

2.2.1 Types and examples of two-sided markets

The theory of two-sided markets was initially conceptualized to explain behavior in credit card markets (Tirole & Rochet 2003), but has quickly been applied to a diverse range of industries. To categorize the different fields of application, Evans & Schmalensee (2008, pp. 669-673) distinguish between four different types:

- *Exchanges and matchmaking activities* (e.g., real estate brokers, dating services)
- *Advertising-supported media* (e.g., magazines, commercial television)
- *Transaction devices* (e.g., payment systems such as credit cards or traveler's checks)
- *Software platforms* (e.g., PC operating systems, video game consoles)

Table 2-3 gives some examples for two-sided markets and indicates the platform intermediary as well as the different sides of the platform.

42 In fact, software platforms are a prime example for two-sided markets (Rochet & Tirole 2003; Evans et al. 2006, pp. 245-274). Depending on the level of integration, software platforms can be thought of as the heart of a one-sided, two-sided or three-sided market, the latter consisting of consumers, software developers and hardware providers (Rysman 2009, pp. 132-133). For expositional simplicity, I restrict the example to a two-sided market.

Table 2-3 **Examples of two-sided markets**

Industry	*Platform*	*Side 1*	*Side 2*
Payment systems	Credit cards (*Visa, MasterCard, American Express*)	Consumers	Merchants
Portable documents	Document standards (*Adobe PDF*)	Readers	Publishers
Employment	Recruitment websites (*Monster.com; jobpilot.de*)	Applicants	Employers
Auctions	Online auction websites (*eBay*); auction houses (*Sotheby's*)	Buyers	Sellers
Scientific publishing	Academic journals (*ASQ, Management Science*)	Readers	Authors
Real estate	Real estate agents; online portals (*ImmobilienScout24*)	Home buyers	Home sellers
Advertising-supported media	Magazines (*The Economist*); commercial television (*RTL*)	Consumers	Advertisers
(Heterosexual) Dating	Online dating websites (*match.com, Parship.de*); nightclubs	Men	Women
Web search	Search engines (*Google*)	Searchers	Advertisers
Games	Video game consoles (*Nintendo Wii, Microsoft Xbox, Sony PlayStation*)	Gamers	Game developers
Video	Analog video formats (*VHS, Betamax*); digital video formats (*Blu-ray, HD-DVD*)	Consumers	Movie studios
Personal computers	PC operating systems (*Microsoft Windows, Apple MacOS, Linux*)	Users	Software developers
Smartphones	Smartphone operating systems (*Google android, Apple iOS, Symbian*)	Users	App developers

As can be seen, two-sided markets cover a wide range of diverse industries. Emphasizing the fundamental unity of very different fields of application is one of the major benefits of the notion of two-sided markets. The following section defines key terms and sheds more light on some important features of two-sided markets.

2.2.2 Key terms and features

Since its introduction by Rochet & Tirole (2000, 2003), the concept of two-sided markets has gained widespread adoption (Evans 2010). Despite its popularity, there is no agreed standard definition, and scholars continue to debate as to what exactly distinguishes a two-sided market from conventional markets.[43] For instance, the term 'two-sided market' may seem redundant at first glance as any market consists of at least two economic actors, i.e., buyers and sellers, that need to interact. However, the notion of two-sidedness stresses the *interdependence* between the actions of the different agents involved. Still, the understanding often remains rather vague.[44] To address this issue, Rochet & Tirole (2006) provide a formal definition that emphasizes the effect of the price structure on the total volume of transactions: "a market is two-sided if the platform can affect the volume of transactions by charging more to one side of the market and reducing the price paid by the other side by an equal amount" (Rochet & Tirole 2006, p. 664-665). In such as market, not only the price level but also the price structure matters, and the Coase theorem does not hold.[45]

The notion of two-sided markets accentuates the role of the intermediating platform. Broadly speaking, platforms are products, services, or technologies that 'connect' the different groups of economic actors and facilitate interaction. Baldwin & Woodard (2009, pp. 19-44) explore the genesis of the term 'platform' and its use by management scholars. They recommend applying the definition coined by Bresnahan & Greenstein (1999, p. 4), which states that a platform is "a bundle of standard components around which buyers and sellers coordinate efforts". Other scholars propose further distinguishing between components and rules. In this sense, components include "hardware, software, and services required by users, along with an architecture that specifies how these components fit together" (Eisenmann 2007, p. 3). Rules include "standards that ensure technical compatibility between components, protocols that govern information exchange … , policies constraining the behavior of network users … and

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43 For a discussion, refer to Rysman (2009, pp. 126-127) and Rochet & Tirole (2006).

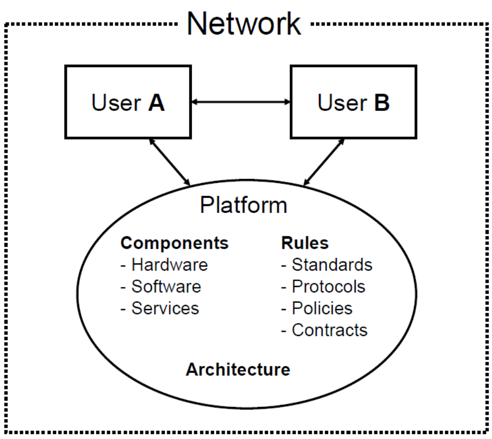
44 Rochet & Tirole (2006, p. 646) criticize that much of the literature has a "'You know a two-sided market when you see it' flavor".

45 Rochet & Tirole (2006, pp. 649-650) provide a more in-depth discussion of why the failure of the Coase theorem is a necessary (but not sufficient) condition for two-sided markets.

contracts specifying terms of exchange and the rights and responsibilities of network participants" (Eisenmann 2007, p. 3).[46]

In two-sided market settings, platforms internalize the network externalities and minimize transaction cost through matchmaking (e.g., real estate brokers), audience-making (e.g., advertising-supported media) or by reducing duplication costs (e.g., software platforms).[47] Figure 2-4 summarizes the stylized relationship between the different groups of users and the platform intermediary in a two-sided market setting.

Figure 2-4 **Components of a two-sided market**
(Source: Eisenmann 2007, p. 3)



Drawing a clear line between two-sided markets and conventional markets is sometimes difficult. As Rysman (2009) notes, virtually all markets can be conceived of as two-sided to some extent. For instance, higher sales of a particular automotive brand may induce local mechanics to acquire more experience with that brand, which could in turn encourage further sales — a two-sided market setting (Rysman 2009, p. 127). However, these cross-side network effects are of negligible importance in determining a market outcome in the automotive industry. As a result,

46 Hence, the notion of platforms goes beyond the concept of (technological) standards: platforms cover the entire business system that evolves around standards. In this context, Evans et al. (2006, p. 54) argue that "standards sometimes give rise to two-sided platforms".

47 See Hagiu (2009, pp. 4-8).

one needs to evaluate the relative importance of two-sidedness in order to assess whether the concept of two-sided markets can be fruitfully applied to a particular empirical case.

It has already been stressed that two-sided markets and indirect network effects are closely related. In general, two-sided markets are a more holistic, actor-centric perspective on indirect network effects, and particularly emphasizes the strategic actions of both sides and the role of the platform intermediary. Furthermore, the concept has highlighted that indirect network effects not only arise due to complementary products, but also when economic agents search for and transact with another type of agent (Gawer 2009, p. 105).

The literature on two-sided markets within the domains of industrial organization, strategy and marketing is rapidly expanding.[48] As such, this introduction can only address certain selected characteristics.

First, indirect network effects give rise to a 'chicken-and-egg' problem for the provider of a platform (Caillaud & Jullien 2003). Consider the example of a video game console: to attract potential buyers, the platform should bring along a wide range of compatible games, but game producers are only willing to develop if there is already a viable user base. Gupta et al. (1999, p. 400) refer to this as "two-way demand contingencies" and argue that managing expectations is key to establishing a successful platform.

Second, two-sided markets usually have a 'subsidy side', which is charged below-cost prices, and a 'money side', which is used to recoup the cost. For instance, *Adobe's Acrobat Reader* is given away for free to consumers, whereas publishers are charged for the *PDF Writer*. Addressing this type of strategic price discrimination, recent works on platform markets address business model design and pricing decisions from the viewpoint of a platform provider (Eisenmann et al. 2006; Rochet & Tirole 2006). Switching perspective, Hagiu & Yoffie (2009) focus on a firm's decision to join a multi-sided platform, the role of strategic and non-strategic players as well as issues of openness and exclusivity.

Third, and most importantly, theoretical and empirical research emphasize that two-sided markets at a mature stage of development are often dominated by a handful of large platforms (e.g., video game consoles such as *Microsoft Xbox*, *Nintendo Wii* and *Sony PlayStation*) or by a single player, such as *eBay* as the leading online auction platform. The reasons for this

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48 A quick analysis using *Google Scholar* shows that there are more than 4,000 publications that give reference to 'two-sided markets' (as of March 2012).

standardization process have already been explored in the discussion of self-reinforcing mechanisms (section 2.1.5.2), namely network effects and other scale economies. This 'winner-take-all' property in particular makes two-sided markets a highly relevant field of study from a path dependence perspective.

Having outlined the theoretical background of this dissertation, I devote the following chapter to the development of the research question.

3 Development of research question

Among the different self-reinforcing mechanisms that have been discussed in the previous chapter, indirect network effects take on a very special role for the emergence of technological lock-ins. This becomes evident when considering the most prominent empirical examples that have been put forward as illustrations of path dependence and technological lock-ins: the emblematic *QWERTY* case, the victory of *VHS* over *Betamax* in the video format war and the dominance of *Microsoft Windows* in the PC industry.

In the early days of typewriters, QWERTY's contingent lead in adoption was reinforced by indirect network effects between firms and typists. Business firms chose QWERTY typewriters, for which trained typists were already available. Viewed from the other side, increasing sales numbers of QWERTY typewriters induced more professional typists to learn to operate this particular keyboard.[49] As a result, the market locked in to the QWERTY standard despite superior alternatives (David 1985).

The video system battle between *VHS* and *Betamax* was heavily influenced by the availability of complementary content. Once *VHS* systems had, by chance and clever strategy, taken a lead in market share, movie studios were more willing to release prerecorded *VHS* tapes instead of supporting the rival *Betamax* format. As a result, consumers benefited from being able to rent or purchase a wider variety of movies. Ultimately, these indirect network effects enforced standardization on the *VHS* technology even though it was perceived to be inferior to the *Betamax* format (Cusumano et al. 1992).

As another example of indirect network effects, PC users are attracted by operating systems that are supported by a rich collection of third-party applications, and application developers favor operating systems that are widely adopted. This positive feedback effect between PC users and application developers essentially explains the lock-in to *Microsoft Windows* in the PC industry, which is often referred to as "everyone's favorite example" (Shapiro & Varian 1999, p. 25) of a dominant standard that may not be the best choice.

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[49] In addition, individual learning effects prevented users from switching to alternative keyboard layouts. As argued in section 2.1.5.2.2, learning effects can explain individual inflexibilities and thus the *maintenance* of a path, but not the *emergence* of a technological lock-in at the market level.

To conclude, in all of these prominent examples of technological path dependence the supposed lock-in was predominantly enforced by indirect network effects. Accordingly, indirect network effects take a prominent position among the other positive feedback mechanisms in explaining technological paths.

Two-sided markets offer a holistic perspective on indirect network effects and thus provide a highly interesting field of study for path dependence theory. The concept focuses on the interactions between various actors that give rise to network externalities. In this regard, the notion of two-sided markets provides an actor-centric view of indirect network effects. Among other examples, operating systems and media standards are widely conceived of as two-sided market settings where different groups of economic actors interact via a technology platform to mutually provide each other with indirect network effects. Two of the most prominent examples for technological path dependence, *Microsoft Windows* and *VHS*, thus fall into the realm of two-sided markets. Theoretical and empirical evidence show that platform competition in two-sided markets often results in a single platform dominating the market. This 'winner-take-all' property makes two-sided markets potential candidates for the occurence of technological lock-ins.

3.1 Research gap and research question

On the basis of Katz & Shapiro's (1985) and Arthur's (1989) seminal contributions, a rich stream of theoretical and empirical research focuses on network effects as the driving force for technological lock-ins. However despite extensive scientific effort, still little is known about the conditions under which network markets tend to get locked-in to *inferior* standards or technologies.

Although it is the foundation for most theoretical research on the topic, Arthur's prominent model of competing technologies (Arthur 1989) does not capture the essence of path dependence theory, which seeks to explain lock-ins to *inferior* technologies. In Arthur's model, neither of the two technologies is defined to be superior or inferior to the other. Instead, any tipping of the market towards a single standard is considered a path-inefficient lock-in. This vague conceptualization of inefficiency stands in sharp contrast to the QWERTY case and other empirical examples, which address the enduring dominance of a particular technology despite superior alternatives.

Only very few other theoretical models focus on technological path dependence in particular. In his seminal paper, Arthur introduces a second, very simplistic model which he himself describes as a "trivial example" (Arthur 1989, p. 119). It lacks the important property of nonergodicity and should thus not be regarded as a model of path dependence in the strict sense. Roedenbeck & Nothnagel (2008) extend Arthur's prominent model but also cannot account for inferior market outcomes. Other models of path dependence are rather general in nature and do not contribute much to the technology context. For instance, the famous Polya urn model is helpful to illustrate the existence of multiple equilibria under increasing returns (Arthur et al. 1994), but it is too abstract to provide conclusions for technological diffusion processes. Other theoretical contributions from the marketing and strategy domain focus broadly on first-mover advantages and market tipping (cf. Dubé et al. 2010; Zhu & Iansiti 2012), but do not genuinely contribute to the literature on path dependence.

To conclude, only few theoretical models specifically address technological path dependence. Furthermore, they are limited in that they cannot explain the dominance of an *inferior* technology, which is at the heart of path dependence theory.

Empirical research on technological path dependence consists largely of qualitative case-by-case analyses, which played a major role in advancing the field. For instance, case study evidence was used to explore technological lock-ins in the realms of keyboard layouts (David 1985), nuclear power technology (Cowan 1990) and home-video standards (Cusumano et al. 1992). However, these historical studies focus on single, supposedly path-dependent empirical cases and were unable to draw general conclusions as to why and under which circumstances network markets end up in a lock-in to an inferior technology.

One of the very few contributions that address technological path dependence in a quantitative empirical study is the work by Tellis et al. (2009). The authors conducted a large-scale empirical analysis of 19 network industries during the 1980s and 1990s and conclude that, in general, the best technology dominates the market and that "path dependence is not that important" (Tellis et al. 2009, p. 147). However, they admit that "an a priori case cannot be made for whether network effects lead to inefficient markets or efficient markets" (Tellis et al. 2009, p. 138).

The uncertainty regarding the causal relationship between network effects and technological lock-ins is inherent in the literature:

> "Markets *may* tend to get locked-in to obsolete standards or technologies" (Katz & Shapiro 1994, p. 108).
>
> "The coexistence of incompatible products *may* be unstable, with a single winning standard dominating the market. In these circumstances, victory *need not* go to the better or cheaper product" (Besen & Farrell 1994, p. 118).
>
> "A technology that by chance gains an early lead in adoption *may eventually* corner the market of potential adopters, with the other technologies becoming locked out" (Arthur 1989, p. 116).[50]

All of these formulations are rather cautious and highlight that (indirect) network effects do not imply 'lock-in determinism'.

Empirical evidence for *Microsoft Windows* and *VHS* as well as theoretical considerations of their 'winner-take-all' character demonstrate that two-sided markets with indirect network effects seem to be prone to the emergence of technological lock-ins. However, of the many markets that are influenced by indirect network effects, only few prominent cases of lock-in have been observed. Despite strong network effects, one finds many examples in which several incompatible technology platforms survive in the battle for market dominance. In other cases, indirect network effects help the 'best' technology platform to become the dominant standard. Obviously, indirect network effects alone do not necessarily lead to inferior market outcomes — there must be something else to explain lock-in phenomena.

To conclude, the conditions under which two-sided markets with indirect network effects lock in to *inferior* technology platforms are not yet fully understood. Given that technology platforms are the "hubs of technology industries" (Economides & Katsamakas 2006, p. 1057) that shape the world in which we live, this research gap is particularly striking. In line with this argument, I raise the following research question:

Research question:
"What are the conditions under which two-sided markets with indirect network effects become locked-in to an inferior technology platform?"

In other words: which circumstances favor, or hinder, the emergence of technological lock-ins in the presence of indirect network effects?

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50 All emphasis is added by the author.

3.2 Focus of the study

In order to better understand the conditions which affect the path-dependent nature of platform competition, I analyze context-specific and actor-specific factors of influence. This serves to refine the broadly defined research question to focus on selected potential determinants of lock-in that are worthwhile to investigate in more detail. The selection was based on two criteria. First, the study focuses on influencing factors that have not been sufficiently addressed by prior research on technological path dependence, but which have shown to be influential in related disciplines, for instance in the two-sided markets literature. In addition, this research sheds light on potential determinants of lock-in for which empirical observations in prominent network industries have called for a more detailed analysis of their potential impact. In essence, the potential factors of influence discussed below have been selected by means of a gap analysis.

3.2.1 Strength of network effects and differences in platform quality

The magnitude of increasing returns is already prominent in the early contributions on technological path dependence. In Arthur's seminal model, the magnitude of increasing returns is represented by the parameters *r* and *s*, which define the level of the absorbing barriers and thus the probability for lock-in (Arthur 1989). Translated to the two-sided market context, the magnitude of increasing returns refers to the strength of the indirect network effects. Usually, indirect network effects are just one source of utility that agents derive from a platform (Economides et al. 2005; Zhu & Iansiti 2012).[51] For instance, PC users benefit from the *inherent value* of the operating system, derived from built-in applications and features, as well as from the *network value*, derived from the availability of compatible third-party software applications. Lemley & McGowan (1998, p. 488) note that "the greater the inherent value … relative to any value added by additional consumers, the less significant the network effect". Accordingly, one needs to measure the strength of indirect network effects relative to the inherent value of a platform. Evans & Schmalensee (2008) argue that there is a positive association between the strength of indirect network effects and industry concentration in two-sided markets. This is

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51 In contrast, some goods are *only* beneficial due to their network value (either direct or indirect) and have no inherent, stand-alone value. They are termed 'system goods' ("Systemgüter", see Weiber 1992).

confirmed by existing models on market tipping (cf. Dubé et al. 2010; Zhu & Iansiti 2012). As a result, the relative strength of indirect network effects is a central element for understanding technological lock-ins in two-sided markets.

When looking at the prominent examples of QWERTY and *VHS*, the (ex-post) debate on whether these cases constitute an inefficient lock-in has largely centered on the level of inferiority of the dominant standard or, in other words, the quality advantage of supposedly superior alternatives. As a consequence, the difference in quality between the competing technology platforms is of crucial importance when investigating technological path dependencies.

To conclude, it can be assumed that the relative strength of indirect network effects and differences in platform quality have a considerable impact on the probability for lock-in. Theoretical and empirical considerations indicate that strong relative network effects and small quality advantages make the dominance of an inferior platform more likely (Suarez 2004). However, while the direction of influence can be anticipated with the current state of research, the precise relationship and the strength of the effects remain unknown. As such, both factors of influence require further attention to better understand the development of technological lock-ins.

3.2.2 Imperfect information and bounded rationality

Despite the importance of seminal contributions by Simon (1955) and others, the role of imperfect information and bounded rationality has not been sufficiently addressed in the context of technological path dependence. The existing theoretical models are built on the premises of rational choice. For instance, in Arthur's model, all agents strictly maximize their individual utility function, so their decisions are completely determined by the given payoff structure. In consequence, agents behave perfectly rationally. In the context of organizational path dependence, Sydow et al. raise concerns that "the assumption of rational choice on the individual level as a starting point is problematic" and argue that an "empirical theory of path-dependent behavior cannot simply ignore the entire research on the boundedness of rationality" (Sydow et al. 2005, p. 10). This is also true for the theory of technological path dependence. Thus, it is time to bring in boundedly rational actors.

Simon's influential paper (1955) on a "behavioral model of rational choice" was an early attempt to substitute the rational economic actor with its boundedly rational counterpart. Simon uses the term 'bounded rationality' to "designate rational choice that takes into account the cognitive limitations of the decision-maker — limitations of both knowledge and computational capacity" (Simon 1997, p. 291; cf. Epstein 2006).

Especially in the early phase of technological diffusion processes, the assumptions of complete information and perfect rationality are not plausible. In an emerging two-sided market, the industry structure is typically fragmented, the long-term prospects of innovative technology platforms are difficult to assess and agents have no previous experience on which to draw. Hence, there is a high degree of uncertainty and agents are unable to make decisions in a perfectly rational manner. Due to the self-reinforcing nature of indirect network effects, two-sided markets are highly sensitive to seemingly insignificant events and suboptimal decisions in the early phase of their emergence. Therefore, elements of bounded rationality and imperfect information may have unexpected enduring consequences for the evolution of an industry. In line with these arguments, the role of imperfect information and bounded rationality needs to be carefully evaluated when exploring the origins of technological lock-ins.

3.2.3 Switching

A thorough analysis of technological path dependence needs to account for the fact that technology choices are not permanent: actors reconsider their former decisions and may switch to alternative technologies. However, existing theoretical research on technological path dependence has not fully addressed this issue. For instance, in Arthurs's model of competing technologies, the agents initially decide on one of the two technologies and are bound to this decision indefinitely. Hence, their choice for a particular technology is never changed nor even reconsidered. This simplifying assumption does not appear valid. In reality, economic actors may cease to use a technology platform and switch to another, either to correct 'wrong' decisions or because a new technology platform with superior quality enters the market. Therefore, economic actors revise their decisions if necessary.

However, inertial forces may hinder switching to another technology platform because the benefits from participating in the 'virtual network' act as a retention mechanism: "With network effects, it can be very difficult to switch horses in midstream to a system that later proves superior" (Katz & Shapiro 1994, p. 106). Friction and delays due to platform-specific resources, such as complementary products or human knowledge, prevent instantaneous switching of platforms. To conclude, when analyzing the conditions under which two-sided markets lock-in to inferior technology platforms, the switching behavior of actors needs to be investigated in detail. Can decisions regarding a particular technology be reversed? Do economic actors regularly reconsider their platform choice? And what is the causal relationship between the switching behavior and the occurrence of technological lock-ins?

3.2.4 Multi-homing

Empirical evidence as well as theoretical insights from the two-sided markets literature reveal that economic actors do not necessarily choose one out of several competing technologies, but rather may choose multiple alternatives. However, the effect of these 'multi-pronged' strategies has not been addressed in the context of technological path dependence. In Arthur's prominent model of competing technologies (Arthur 1989), each agent is faced with the choice between technology A or B. However, in many two-sided markets, economic actors simultaneously use several competing technology platforms, which is termed "multi-homing" (Rochet & Tirole 2003; Armstrong 2006). In this case, actors do not choose either A *or* B, but instead A *and* B. For instance, software developers can develop their applications for *Windows* and *Mac* ('multi-homing'), instead of supporting one software platform only ('single-homing'). In many cases, the ability to multi-home differs between the different sides of the platform. For instance, consumers typically had either a *VHS* or a *Betamax* video system at home, whereas movie studios in principle could release titles in both competing formats. Supporting multiple platforms may be beneficial but costly, and the cost of multi-homing largely depends on the degree of compatibility between the technology platforms. To conclude, it is believed that the opportunity for multi-pronged strategies of supporting several platforms is likely to affect technological path dependencies. As a consequence, the impact of multi-homing must be analyzed in order to better understand the circumstances for technological lock-ins in the presence of indirect network effects.

In summary, I have argued that the conditions under which two-sided markets with indirect network effects lock-in to inferior technology platforms are not yet fully understood. After having identified this research gap, a number of context-specific and actor-specific factors of influence were proposed for further research. The following chapter now discusses the methodological approach that is best suited to answer the research question posed by this dissertation.

4 Research methodology

The present chapter elaborates on the choice of social simulation as a research method to investigate the conditions for path dependence in two-sided markets. The early contributions on technological path dependence which established the field mostly relied on analytical models (Arthur 1983; Arthur 1989; Arthur 1994). Their initial findings were taken up by a wealth of qualitative case studies, for instance by David (1985), Cowan (1990) and Cusumano et al. (1992). The seminal works from both methodological streams have already been addressed in chapter 2. While acknowledging the contributions from qualitative research, Vergne & Durand (2010) suggest “moving away from historical case studies of supposedly path-dependent processes” and argue for the use of more controlled research designs. Drawing on epistemological considerations, they emphasize the benefits of laboratory experiments (Bach 2008; Koch et al. 2009; Langer 2011), counterfactual investigation of causal relationships (Durand & Vaara 2009) and computer-based simulation (Sterman & Wittenberg 1999; Hardenacke 2005; Roedenbeck & Nothnagel 2008; Petermann 2010). Stressing the unique benefits of social simulation research, Garcia (2005) also supports the view that computer-based simulation is ideally suited to trace the complex mechanisms of unfolding lock-in processes of path dependence. In line with these arguments and the specific requirements of the research question, I apply an empirically grounded agent-based simulation approach. The reasons for this methodological choice are outlined in the following paragraphs, together with a phase model of simulation research in the social sciences.

4.1 Rationale for choosing a simulation approach

The selection of an appropriate research methodology is crucial for addressing the research problem that was identified in chapter 3. As such, one needs to carefully evaluate the particular advantages and limitations of the available instruments against the background of the research problem. The posed research question (the conditions for path dependence in two-sided markets) and the focus of the study (selected factors of potential influence, see chapter 3.2) impose certain requirements on the research design:

- The research design needs to incorporate a *longitudinal perspective on indirect network effects* and competing technological platforms. The interaction between the various market participants, which is the origin of indirect network effects, needs to be explicitly represented.
- The research design needs to incorporate *small events* that can trigger a contingent lead of a technological platform.[52] Consistent with prior path dependence research, contingency refers to "unpredictable, non-purposive, and seemingly random events" (Vergne & Durand 2010, p. 755). The research design should be able to justify that these small events are indeed random and not caused by structural forces outside the attention of the researcher.[53]
- The research design needs to incorporate the concepts of *bounded rationality* and *imperfect information,* which are supported by existing empirical research on how humans process information and form decisions.
- The research design needs to incorporate *diffusion processes* and *opinion dynamics* by taking into account interpersonal communication and social networks.
- The research design needs to cover a time horizon long enough to *observe a possible lock-in* at the market level. Furthermore, the occurrence of lock-in should be precisely defined. Consistent with prior research on technological path dependence, the research design should be able to justify the claim of sub-optimality of the dominant technological platform in the lock-in stage.[54]

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52 In order to speak of path dependence, it is important to show the contingent character of the processes under review. If contingency holds, there must be multiple possible equilibria. In such cases, the outcome of the process can be attributed to path-dependent dynamics that "select an equilibrium from several candidates, by the interaction of economic forces and random historical events" (Arthur 1989, p. 128). Otherwise, in the case that there is only one stable equilibrium, the process behaves deterministically and is not path-dependent. Instead, the initial conditions completely predetermine the outcome of the process.

53 See Vergne & Durand (2010) for a thorough debate on the verifiability and falsifiability of contingency.

54 Research on organizational path dependence often incorporates a weaker definition, speaking instead of "potential inefficiency" (Sydow et al. 2009). However, most literature on technological path dependence invokes a strong form of the inefficiency argument which claims that there is a superior technological solution that would increase utility at the aggregate level.

- Finally, the research design should be able to clearly identify the *causal link* between the explanatory variables and the occurrence of lock-in, thereby excluding other possible explanations.

Having described the methodological requirements, I will now briefly outline the available research methods, discuss their suitability for the research question at hand and thereby substantiate the choice in favor of computer-based simulation.

In simple terms, scientific progress relies on two general methodologies: (1) theoretical analysis or *deduction,* and (2) empirical analysis or *induction*. Deductive reasoning is based on a set of assumptions, often stated as mathematical relationships. Conclusions are then deduced through mathematical proofs or derivation (Harrison et al. 2007), and hypotheses are formed which are tested against empirical data. In contrast, inductive reasoning is based on empirical observations that are used to identify patterns and regularities. In the following, I elaborate on the suitability of various deductive and inductive research methods against the background of the posed research question.

Deductive research approaches

Analytical models are one form of deductive reasoning which is often applied in the field of economics and management studies. However, analytical models are constrained by the need to make them "mathematically simple enough to be used as building blocks for higher-level aggregations (e.g., market outcomes)" (Ho et al. 2006, p. 341). For instance, many of the existing theoretical results on two-sided markets, predominantly in the industrial organization literature, rely on quite abstract analytical models of how industries operate and different platforms compete (Caillaud & Jullien 2003; Armstrong 2006; Economides & Katsamakas 2006). These models are limited by nature as they have difficulties in capturing the inherent complexity of social processes (Gilbert & Troitzsch 2005). Market structures and competitive dynamics are the result of an interaction among multiple interdependent processes with stochastic elements that are often mathematically intractable (Harrison et al. 2007; Galán et al. 2009). Furthermore, it is

See also Vergne & Durand (2010) for a methodological discussion with regard to the sub-optimality claim.

believed that this limitation of analytical models has constrained researchers in incorporating elements of bounded rationality, which require a more sophisticated modeling of the underlying cognitive processes (Harrison et al. 2007). However, in order to address the research question at hand, a careful consideration of bounded rationality and imperfect information seems crucial, especially to enhance our understanding of the role of contingency and small events in the early phase of industry evolution. In light of these arguments, while analytical models may benefit from the elegance and "supreme beauty" of mathematical proofs (Russell 1910, p. 73), they may ignore crucial characteristics of the underlying system. In a criticism on his own field, Leontief (1982, p. 104) argues that a large part of the economic literature has developed a "nearly irresistible predilection for deductive reasoning" that lead the reader "from sets of more or less plausible but entirely arbitrary assumptions to precisely stated but irrelevant theoretical conclusions". This criticism is supported by May (2004, p. 793) who remarks:

> "Perhaps most common among abuses, and not always easy to recognize, are situations where mathematical models are constructed with an excruciating abundance of detail in some aspects, whilst other important facets of the problem are misty or a vital parameter is uncertain to within, at best, an order of magnitude. It makes no sense to convey a beguiling sense of 'reality' with irrelevant detail, when other equally important factors can only be guessed at."

With regard to the research question, analytical models are not suited to account for the complex interdependencies among economic actors and their decisions that give rise to indirect network effects. Analytical approaches fall short of modeling the impact of random small events and fail to take a longitudinal perspective on unfolding lock-in processes. Furthermore, interpersonal communication and opinion formation have a profound impact on the diffusion dynamics of technological innovations. Analytical models can only represent these dynamics at a very elementary level and are difficult to incorporate in a broader, macro-model of platform competition in two-sided markets. As a result, an analytical model is an unsuitable tool for the research question at hand.

Hypothesis testing involves deriving hypotheses from existing theory through logical reasoning and then by confirming or rejecting these hypotheses based on quantitative empirical data. Leaving aside its benefits and shortcomings, hypothesis testing must be regarded as the current mainstream methodological paradigm in the social sciences, closely connected with *scientific realism* as the dominant philosophical foundation (Causay 1979; Leplin 1984).[55] Hypothesis testing can be either done using cross-sectional or longitudinal data, or with a combination of both as in panel studies. Cross-sectional quantitative studies examine existing variations in the independent variables(s) to explain the variation in the dependent variable at one point of time. As path dependence theory is a process theory, a cross-sectional design is incapable of observing the self-reinforcing nature of indirect network effects over time. A longitudinal quantitative study, on the other hand, raises serious questions of data availability and data precision. Data collected *ex post*, for instance on the market shares of competing technological platforms, has a level of detail that is insufficient for a thorough analysis of the underlying mechanisms. Furthermore, the contingent character of a single 'small event' that may cause a technological lead is impossible to verify in a large-scale longitudinal design — perhaps the platform's technological lead is not at all contingent, but rather the result of structural forces outside the attention of the researcher (Vergne & Durand 2010)? Lastly, to better understand the impact of context-specific and actor-specific conditions for path dependence in two-sided markets, a quantitative empirical design requires a large number of comparable cases that share the same characteristics *but* differ in exactly one property. In this regard, technological standardization battles are difficult to analyze in the context of a large-scale empirical project. Because all of these processes possess very different characteristics, it is difficult to distill the impact of individual factors given the limited number of cases. This issue leads to the problem of causality: 'correlation proves causation' is a logical fallacy often found in quantitative empirical research, which by its nature is unable to establish an unequivocal causal relationship between cause and effect (de Vaus 2003). Instead, quantitative empirical research infers, rather than observes, causal relationships.[56] However, the identification of a clear causal link between the

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55 Without entering the debate of philosophy of science: Carrier (2004, p. 140) characterizes *scientific realism* by two principles: (1) theoretical terms in the mature sciences typically refer to real objects; (2) theoretical laws in the mature sciences are typically approximately true (Putnam 1978, pp. 20-21). Apart from these two shared principles, Leplin (1984, p. 1) notes that "scientific realism is a majority position whose advocates are so divided as to appear a minority".

56 Hence, quantitative research designs aim to "improve the quality" (de Vaus 2003, p. 34) of causal inferences. De Vaus (2003) differentiates between probabilistic and deterministic concepts of causation. In order to assert that variables are causally related, the author lists four

explanatory variables and the occurrence of path dependence is at the heart of this dissertation. In conclusion, hypothesis testing based on large-scale quantitative empirical data does not satisfy the requirements of the research question laid out in chapter 3.

Experimental designs can help to mitigate the problem of causality and have been applied successfully for path dependence research (Bach 2008; Koch et al. 2009; Langer 2011). However, as the research question at hand is concerned with path dependence at the market level, a laboratory experiment would need to bring together a group of representative actors from the industry to model the emergence of a network effect market, including platform providers, content developers and consumers. Such a research design could yield interesting conclusions with high internal and external validity. Nevertheless, achieving sample representativeness does not seem feasible. In light of this challenge, it comes as no surprise that prior experimental studies focused solely on path dependence at the *individual* level, conducting experiments with student participants only.[57] However, such an approach is inadequate to analyze technological lock-ins that primarily occur through the interaction of competing business firms.

Inductive research approaches

In the social sciences, inductive arguments draw on case-based empirical evidence to form generalizations and are perceived as a method for theory building (Eisenhard & Graebner 2007; Yin 2009). Case study research is an important inductive method and has played a major role in advancing the theory of technological path dependence. For instance, case study evidence was used to explore lock-ins in the realms of keyboard layouts (David 1985), nuclear power technology (Cowan 1990) and home-video standards (Cusumano et al. 1992). However, despite these successful applications of the case study methodology for path dependence research, two main issues argue against a case study analysis.

First, exploring the conditions for path dependence in two-sided markets would require a *comparative* case study design. The replication logic involved in such a design is central to case

criteria that must be met: co-variation, time order, capability of change of the dependent variable and theoretical plausibility of the causal relationship (de Vaus 2003, pp. 34-36).

57 See also footnote 122 on page 171 regarding the problematic use of student samples.

study research (Eisenhardt 1989): similar to a series of related laboratory experiments, multiple cases behave "as discrete experiments that serve as replications, contrasts, and extensions to the emerging theory" (Eisenhardt & Graebner 2007, p. 25). However, a thorough analysis of well-known historical cases of technological path dependence driven by indirect network effects, i.e., *Windows* vs. *Apple* and *VHS* vs. *Betamax*, revealed that these cases do not possess enough similarities to be used in a comparative case study analysis of platform competition in two-sided markets. Furthermore, these historical cases already seem to have been exhaustively studied from a path dependence perspective. In principle, historical cases could also be compared with a contemporary standardization battle. However, addressing a phenomenon in the making appears very challenging, as the duration and outcome of the process are unknown ex-ante. For instance, the diffusion of innovation, potentially leading to a technological lock-in, often takes many years to complete, making a continuous observation impractical for a dissertation project.

Second, Vergne & Durand (2010) argue convincingly against the use of historical case studies of supposedly path-dependent processes. Drawing on epistemological considerations, they question whether empirical case studies can verify or falsify the contingency assumption of path dependence. Based on mathematical reasoning by Chaitin (1975) and Gödel's incompleteness theorem (Gödel 1931), Vergne & Durand point out that randomness cannot be verified or even proved in a complex social system by means of *ex post* empirical evidence. A supposedly contingent technological lead in an adoption process could always be attributed to properties outside the attention of the researcher.[58] Hence, as alternative explanations cannot be ruled out, cases of path dependence can always be challenged by arguing against the "chancy character of an adoption pattern" (Vergne & Durand 2010, p. 746). In this regard, case study research has difficulties in clearly identifying the causal link between the explanatory variables and the occurrence of technological lock-ins. This issue calls for a more controlled research design in order to explore the conditions for path dependence in two-sided markets.

[58] In fact, this has been a frequent argument against path dependence theory. For instance, in the VHS controversy, Arthur (1990) attributes the dominance of VHS to a contingent lead in the adoption process. Liebowitz & Margolis (1995) contest this interpretation by highlighting the importance of the longer recording time of VHS, a property not considered by Arthur.

Computer-based simulation

Computer simulation addresses many of the shortcomings of the alternative research methodologies discussed above. It is defined as "a method for using computer software to model the operation of 'real world' processes, systems, or events" (Law & Kelton 1991, p. 1). As a variant of deductive research, computer simulation allows to draw deductive conclusions from a set of explicit assumptions in cases where an analytical solution is difficult, impossible, or, where possible, incommunicable.[59] However, simulation models do not prove theorems (Axelrodt 1997). Instead, they generate 'virtual' empirical data which can be analyzed inductively to uncover unknown relationships among the variables. In this sense, simulation complements both inductive and deductive research methodologies and is by no means a substitute.

For most economic processes there is no way to manipulating a real world system to answer 'what if' questions. In other settings, empirical data may be unavailable or not yet available. In each case, simulation techniques can help to explore the effect of changing system parameters over time in an artificial environment. In this sense, simulation research enables the researcher to conduct virtual experiments: a certain aspect of the modeled reality is manipulated and the resulting effect on the system's state can be observed. Hence, computer simulation is defined as "a computational model of system behavior coupled with an experimental design" (Harrison et al. 2007, p. 1234). The benefit of this experimental approach is its ability to establish a clear causal relationship between the variables under review (Field & Hole 2003).

It has been stressed that the research question demands a longitudinal perspective on the emergence of technological lock-ins driven by indirect network effects. Computer-based simulation is ideally suited for this task because dynamic models of path-dependent processes can be analyzed at any desired level of detail (Davis et al. 2007). This methodology provides a highly controlled research environment in which one can fully define the model environment, its initial conditions, the level of contingency as well as the self-reinforcing mechanisms that are at work (Vergne & Durand 2010). Zott (2003) also emphasizes the potential for path dependence research by highlighting that simulations "allow researchers to generate multiple historical trajectories emanating from the same set of initial conditions, thus enabling them to generalize about the mechanisms and processes that produce such histories" (Zott 2003, p. 109). In addition

[59] I am indebted to Klaus Troitzsch for pointing this out.

to exploring the impact of contingency in otherwise identical conditions, simulations can be re-run multiple times with varied system parameters, i.e., under different initial conditions. In this regard, computer-based simulation fully satisfies the requirements of the research question: in a two-sided market environment, a simulation model allows to explore potential factors of influence (e.g., bounded rationality, multi-homing, or switching; see chapter 3.2) that may increase or decrease the likelihood of a technological lock-in. Thus, computer-based simulation can be regarded as an ideal methodology to refine our understanding of technological path dependence.

To conclude, simulation helps to overcome the dichotomy between real world complexity and the oversimplified abstraction level of analytical models. Compared with analytical models, computer simulation allows for more realistic assumptions rather than forcing the researcher to "compromise with analytically convenient ones, as is common in deductive theory" (Harrison et al. 2007, p. 1230), for instance perfect rationality, homogeneity of economic actors, etc. Compared with qualitative research methods, simulation models benefit from the theoretical rigor enforced by formal modeling. As Harrison et al. (2007, p. 1233) state: "a process may appear to be well understood, but an attempt to specify an equation for the operation of the process over time often exposes gaps in this understanding". Therefore, simulation models can contribute to both inductive and deductive research methodologies and are recognized as a "third way of doing science" (Axelrod 1997).[60]

The process of conducting simulation research and its embedding in the scientific process will be discussed in more detail in section 4.3. However, I will first elaborate on the choice of the specific simulation method in light of the requirements of the research question.

4.2 Choice of simulation method: Modeling the forest or modeling the trees?

Computer simulation is an umbrella term for a variety of simulation methods that are used in physics, biology, engineering, psychology, economics and many other fields. Gilbert & Troitzsch (2005) differentiate between seven simulation techniques that are most prominent in the social

60 In a conceptually similar vein, Ostrom (1988, p. 381) argues that simulation "offers a third symbol system" for expressing theoretical ideas, after natural language and mathematical notation.

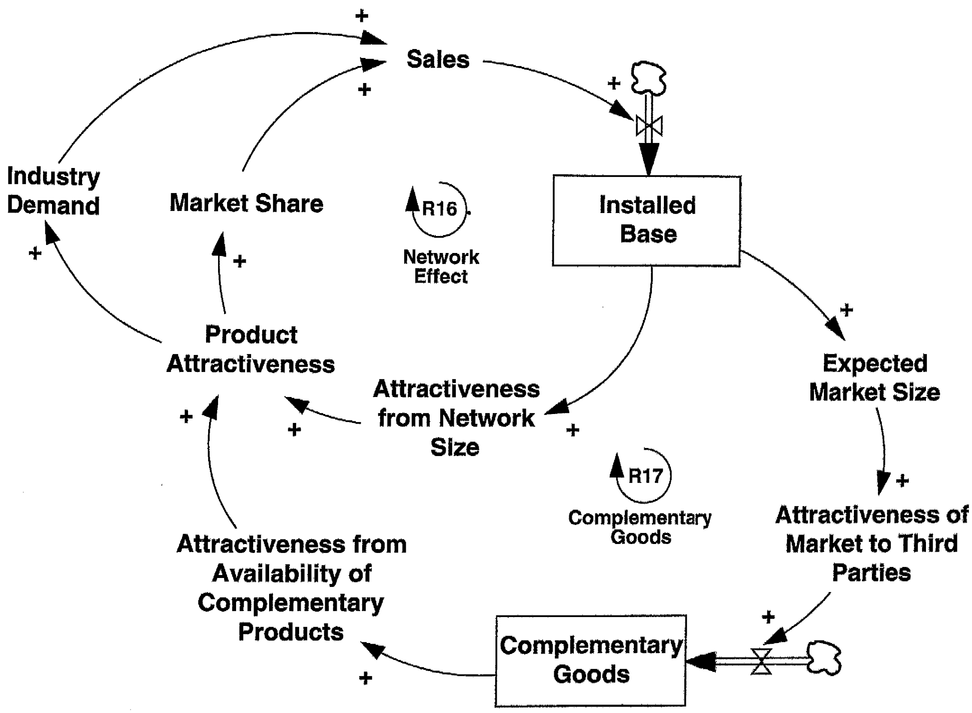
sciences.[61] Drawing up a shortlist, the present section highlights the key aspects of s*ystem dynamics* and a*gent-based simulation*, the two most commonly used methods in the fields of management and economics.[62]

System dynamics models attempt to capture the behavior of a complex system as a whole rather than modeling the individual behaviors and properties of agents within the system (Harrison et al. 2007). System dynamics techniques were originally developed in the mid-1950s, primarily by Jay W. Forrester (1958) at the MIT *Sloan School of Management*, and became widely prominent when the Club of Rome published *The Limits to Growth* (Meadows 1974) following their WORLD3 model in 1972. System dynamics approaches take a macro perspective on systems and assume a high level of aggregation of the modeled entities (Gilbert & Troitzsch 2005). The dynamics of a target system are modeled using stock and flow variables which represent internal feedback loops. A stock variable denotes any entity that accumulates or dissipates over time, whereas a flow variable describes the rate of change in a stock (Schieritz & Milling 2003). To illustrate the concept, Figure 4-1 depicts a stock and flow diagram for a two-sided market driven by indirect network effects (Sterman 2004).

61 The seven approaches discussed are: system dynamics and world models; microanalytical simulation models; queuing models; multi-level simulation; cellular automata; multi-agent modeling; and learning and evolutionary models (Gilbert & Troitzsch 2005, pp. 28-198). See also Davis et al. (2007, p. 486) for a systematic comparison of five simulation approaches used in management research: system dynamics, NK fitness landscapes, genetic algorithms, cellular automata, and stochastic processes.

62 See Schieritz & Milling (2003), who coined the phrase "modeling the forest or modeling the trees", for a more detailed comparison of system dynamics and agent-based simulation.

Figure 4-1 **System dynamics model of a two-sided market**
(Source: Sterman 2004, p. 371)



The displayed two-sided market model comprises a direct network effect (feedback loop "R16") as well as an indirect network effect (feedback loop "R17") based on the availability of complementary goods. The installed base[63] and the number of complementary goods are represented by two stock variables which increase/decrease according to the inherent dynamics denoted by various flow variables. For instance, the number of complementary third-party products for a particular platform, depends on the expected market size, i.e., the installed base of consumers. Complementary products increase the platform's attractiveness, which in turn drives up sales and market share.

This model provides a solid starting point for modeling path dependence in two-sided markets. In fact, Sterman specifically tailored the model to the VCR industry and the battle of PC operating systems (Sterman 2004, p. 370), two very prominent examples of technological lock-ins. However, a system dynamics model has some serious restrictions that limit its

[63] Installed base is a metric that measures the number of units *in use*. In contrast, market share refers to a platform's percentage of total *sales* over a specific period of time.

usefulness for the research question at hand. First, macro-level phenomena such as the emergence of a new industry are typically very complex. This makes it problematic to directly specify the inherent feedback loops in the system from an aggregate viewpoint. Even when the general direction of a feedback loop is well understood, for instance the indirect network effect between complementary products and the installed base as described above, the *quantification* of the flow variable that represents the relationship between the stock variables poses a serious challenge to the researcher. In a system dynamics model, the level of aggregation of the objects being modeled is often simply too high to form valid, empirically sound assumptions. Second, system dynamics models abstract from single events and entities (Schieritz & Milling 2003). In this regard, a system dynamics approach is well suited to model self-reinforcing mechanisms, but has difficulties in representing the impact of 'small events' in a path-dependent process. Third, competition in a two-sided market arises from the interaction of different groups of economic actors. As it is the origin of indirect network effects, the interaction between the various market participants should be explicitly represented in the research design. However, by taking a macro perspective, system dynamics models are unable to account for the role of interpersonal communication and the topology of social networks, which are crucial for incorporating diffusion processes and opinion dynamics.

Agent-based simulation (ABS)[64] is a relatively new method for modeling complex adaptive systems[65] from the "bottom up" (Axelrod 1997) through the use of interacting, autonomous agents (Macal & North 2010). Agent-based simulation models emphasize the

64 Various similar terms and abbreviations are used in the literature: agent-based modeling (ABM), agent-based modeling and simulation (ABMS) and multi-agent based simulation (MABS).

65 The idea of complex adaptive systems emanated from the Santa Fe Institute in the late 1970s. Holland (in: Waldorp 1992, p. 145) provides an operational definition: "A Complex Adaptive System (CAS) is a dynamic network of many agents (which may represent cells, species, individuals, firms, nations) acting in parallel, constantly acting and reacting to what the other agents are doing. The control of a CAS tends to be highly dispersed and decentralized. If there is to be any coherent behavior in the system, it has to arise from competition and cooperation among the agents themselves. The overall behavior of the system is the result of a huge number of decisions made every moment by many individual agents." CAS examples include decentralized market economies (Tesfatsion 2003), the human immune system and political parties, among many others. See also Anderson (1999) for a discussion of complexity theory and organization science.

micro-level interactions between agents as the primary unit of study, as opposed to the system dynamics approach, which models systems from an aggregate, macro-level view. Gilbert (2008, p. 77) describes agents as distinct parts of a computer simulation model that represent *autonomous* social actors such as individual people or organizations. Agents interact with each other as well as with the simulation environment according to their rules of behavior, which can be "simple or complex, deterministic or stochastic, fixed or adaptive" (Billari et al. 2006, p. 3).

The central property of agent-based models of complex systems is emergence (Holland 1998). Rather than being directly modeled, the macro-scale behavior of the social system *emerges* from the actions of the constituent agents and their interactions in the simulation environment (Harrison et al. 2007). In the presence of nonlinearities, the system's behavior cannot be predicted from an understanding of the components.

Historically, agent-based simulation models have followed the genetic algorithms[66] and cellular automata[67] simulation approaches. With the improvements in computing technologies since the 1990s, agent-based simulation has become increasingly popular in the social sciences, including economics, political science, sociology, geography and demography (Gilbert 2008). This is due to a number of unique benefits offered by this type of simulation:

1. The modeling of heterogeneous agents living in a controlled environment allows a realistic representation of real-world phenomena without the simplifying assumptions of homogeneity or average behavior (Gilbert 2008; Garcia 2005).
2. The communication and local interactions between agents can be explicitly simulated (Gilbert 2008). For instance, the role of social network topologies has been found to be very influential in diffusion dynamics (see for example Watts & Strogatz 1998).
3. Most social processes do not follow a deterministic pattern, but rather include some form of contingency. Agent-based models can easily incorporate stochastic decision

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66 In a genetic algorithms model, agents follow a Darwinian framework of evolution and adapt to an optimal agent form via mutation and crossover mechanisms (Davis et al. 2007).

67 In a cellular automata model, space is represented as a uniform grid. Cells change their states as a function of their previous state and local interaction with other cells (Gilbert & Troitzsch 2005). If cells are viewed as agents, cellular automata models can be regarded as a rudimentary form of agent-based models, as noted by Harrison et al. (2007).

processes at the individual decision-making level, as opposed to adding abstract noise terms at the system level as is frequently used in other types of models (Garcia 2005).

4. Agent-based models allow the incorporation of boundedly rational actors who are limited in their cognitive abilities, much like human beings. This is also highlighted by Epstein (2006, p. 38): "agent-based modeling is clearly a powerful tool in the analysis of … autonomous actors with bounded information and computing capacity". As such, agent-based models can address the call by Simon (1955) and others to substitute the rational economic actor with its boundedly rational counterpart.
5. Agent-based modeling follows the natural human thought process: there is a direct relation between entities in the real-world and computational agents in the model. This "ontological correspondence" (Gilbert 2008, p. 14) in an agent-based model makes it easier for the researcher to design the model and interpret its outcome. Furthermore, this correspondence facilitates the integration of qualitative and quantitative findings to determine the agents' rules and decision logics in order to enhance external validity at the micro level.

Having outlined the concept of agent-based simulation, I now relate the unique features of this methodology to the specific requirements of the research question on the conditions for path dependence in two-sided market. Table 4-1 summarizes the benefits of agent-based simulation in general and links them to the related dimensions of the research project at hand.

Table 4-1 **Benefits of agent-based simulation and related dimensions of the research question**
(Source: left column partly draws on Garcia 2005, p. 383)

Agent-based simulation is particularly useful…	*Related dimension of the research question*
…when the research question addresses 'what if' scenarios;	The research project aims to analyze the occurrence of technological lock-ins under different structural and actor-related conditions in a controlled research setting.
…when a longitudinal perspective is requested;	Path dependence is a process-oriented theory that requires a longitudinal research design in order to trace the sequence of decisions and events.
…when both macro- and micro-level of analyses are of interest;	Individual decisions of market participants (micro-level) and the feedback mechanisms between them are crucial to understand technological lock-ins (macro-level).
…when emergent phenomena may be observed;	The emergence of technological lock-ins cannot be understood by an isolated analysis of the subsystems.

Agent-based simulation is particularly useful…	*Related dimension of the research question*
…when contingent events play a crucial role;	The research question calls for modeling small events, which may cause a contingent lead of a technological platform, at the individual decision-making level.
…when the population is heterogeneous and/or the topology of the interactions is complex;	Heterogeneous preferences, interpersonal communication and the role of social networks have a profound impact on the diffusion dynamics of technological innovations.
…when bounded rationality and imperfect information need to be incorporated.	The research question explicitly addresses the impact of bounded rationality and imperfect information on the emergence of technological lock-ins.

To conclude, in light of these arguments, an agent-based simulation approach is the method of choice for addressing the research project at hand. As highlighted by Vergne & Durand (2010), computer-based simulation is very well suited to investigate path-dependent processes from a longitudinal perspective in a controlled research setting. In particular, agent-based simulation allows to explore technological lock-ins in a two-sided market setting which emerge as the macro-level result of the decisions and interactions of individual market participants. In this regard, agent-based simulation provides new opportunities for better understanding technological path dependence from the bottom up.

4.3 The process of simulation research

The present section elaborates on the role of simulation research in the scientific process, discusses the uses and limitations of the method, and describes the different stages of the simulation project. A proposed phase model of simulation research is also presented, which will determine the structure of the upcoming chapters of this dissertation.

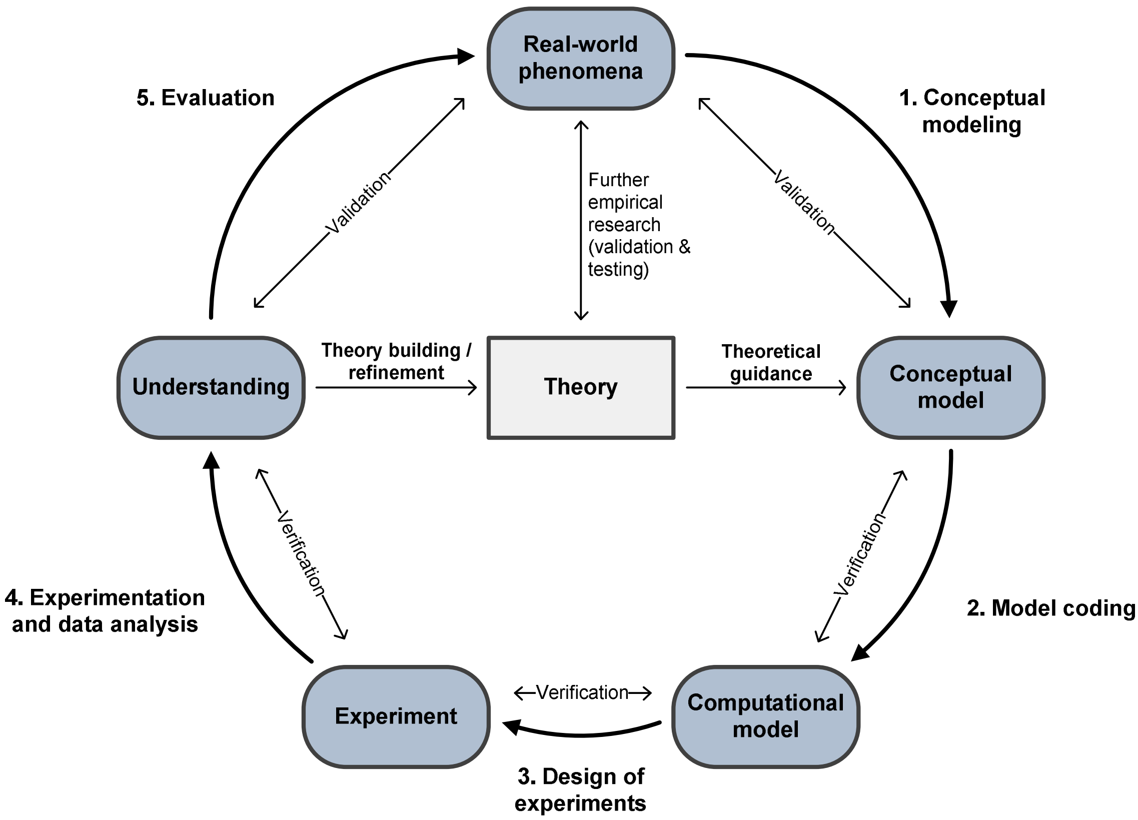
Simulation is particularly useful in the "'sweet spot' between theory-creating methods using such methods as inductive multiple case studies … and formal modeling …, and theory-testing research using multi-variate, statistical analysis" (Davis et al. 2007, p. 481). Instead of predicting empirical phenomena or proving theorems, simulation helps to refine theories by uncovering theoretical relationships, which can be examined by further empirical evidence (Bonabeau 2002).[68] In this regard, computer-based simulation presents a "learning tool to guide

68 See also Harrison et al. (2007, pp. 1238-1240) for an account of the various purposes of simulation research in organizational and management research.

intuition" in refining theories (Garcia 2005, p. 382), especially when the theoretical focus is on a process perspective and when the phenomena involve multiple interacting processes with nonlinearities. Referring back to the research question, this dissertation applies an agent-based simulation to uncover, and specify more precisely, the relationship between potential context- and actor-specific factors of influence and the emergence of technological lock-ins in a two-sided market setting. Thus, simulation modeling is used here as an explorative research method to refine the theory of technological path dependence.

The process of simulation research in the context of theory building and refinement is best understood by means of a phase model, as illustrated in Figure 4-2.[69]

Figure 4-2 **Phase model of simulation research**
(Illustration based on Wijermans 2011; Harrison et al. 2007; Helmhout 2006; Robinson 2004; Balci 1998)



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[69] For an in-depth discussion of epistemological perspectives on simulation, please refer to a special issue of the *Journal of Artificial Societies and Social Simulation* (Vol. 8, No. 4).

The process of social simulation research can be briefly described as follows. First, a conceptual model is formed based on existing theory and with reference to an empirical phenomenon that is to be explored. This conceptual model is transformed to a computer model which is used to conduct virtual experiments. By analyzing and interpreting the experimental data, a better understanding of the 'hidden' causal relationships among the constructs is achieved, which then contributes to theory building and refinement. Lastly, the simulation results can be compared to empirical data in order to enhance the external validity of the model. Furthermore, the derived theoretical relationships can be examined with additional empirical evidence and deductive hypothesis testing. The different stages of the phase model of simulation research are discussed in detail below.

4.3.1 Phase 1: Conceptual modeling

In the first phase, a conceptual model of some real-world entity or phenomenon is developed, guided by existing theory and empirical research. Modeling in general has a long history in the social sciences, much longer than the use of computing technology, and became a well-established research method with the introduction of powerful statistical methods to analyze large amounts of quantitative empirical data (Gilbert 2008).[70] However, simulation modeling as a form of computational social science is a rather new methodology, first introduced in the 1960s and more widely used since the 1990s (Gilbert & Troitzsch 2005).

In general, any model serves as a "representation of social reality" (Gilbert 2008, p. 2), embodying the *essential* structure of some target object in the real world. In this sense, a model is always a simplification, as it is by definition "smaller, less detailed, less complex, or all of these together" (Gilbert & Troitzsch 2005, p. 2) compared to the target. As a consequence, "it is natural to have several different models of the same thing, each of which considers a different aspect" (Lave & March 1993, p. 3). The conceptual modeling phase refers to the process of representing the problem verbally, logically and/or mathematically. The design of an agent-based simulation model involves two steps: (1) the discovery of the relevant agents, and (2) the discovery of the agents' behaviors (North & Macal 2007). Probably the most difficult part of simulation research

[70] These early models, however, were largely unable to address the processual and nonlinear characteristics of social phenomena.

is to decide on the complexity level of the model. Model design always involves a tension between simplicity and elaboration (Harrison et al. 2007), and one has to keep in mind that a model is meant to be an abstraction and approximation. As with any formal model, the aim is to construct a (most) simplified representation of the real world which incorporates all the key elements to understand the process under review. Rahmandad & Sterman (2008, p. 1013) call for a balance in model development "among detail, scope, and the ability to carry out sensitivity analysis over the inevitable uncertainties we all face". For this purpose, Harrison et al. (2007) propose an iterative process where the researcher has to continuously balance the cost and benefit of the added complexity. This challenge is not specific to simulation-based research, but rather applies to formal modeling in general. As Ho et al. (2006, p. 344) put it: "The greatest challenge for modelers is weighing the benefits of adding parameters against the criteria of simplicity and model elegance". Classical economics teaches us that the optimal complexity level is reached when the marginal value of descriptive and predictive power equals the corresponding marginal cost of model complexity, e.g., in terms of transparency and computational handling. As is often the case with classical economic reasoning, in practice this rarely gives a clear-cut answer on when to stop increasing model complexity, but nevertheless provides an analytical way of thinking about the issue. Nelson & Winter (1982, p. 402) conclude: "Artful simplification is the hallmark of skillful modeling".

Parallel to the modeling phase is the continuous process of *validation*. Conceptual model validation refers to the process of checking whether the model provides an adequate, although not necessarily accurate, representation of the target. Are the micro-foundations, i.e., the agents' behavior amd decision heuristics, based on empirically sound assumptions (Fagiolo et al. 2007)? Does the model meet the objectives of the research question? Are the model's entities, structure and causal relationships "reasonable for the intended purpose" (Sargent 2000, p. 50)? Is the model architecture still in line with the underlying theory?

Despite the many benefits of simulation research, there are also some drawbacks. Compared to analytical models, agent-based models are necessarily more complex in structure. In general, they incorporate more entities with more properties, which interact in a dynamic environment over a period of time according to sophisticated decision rules. These characteristics make agent-based models "more difficult to analyze, understand and communicate compared to analytical models" (Grimm et al. 2006, p. 116), which has led to some hesitation regarding agent-based simulation in the scientific community.

Apart from a general "lack of clarity about the method" (Davis et al. 2007, p. 480), the controversy can be largely attributed to the absence of clear, complete and concise communication. Quite frequently, simulation projects appear as 'black boxes', as criticized by Harrison et al. (2007). Hales et al. (2003) complain that agent-based models are "rarely compared, built-on or transferred between researchers" and that it is "difficult to replicate simulation models". As science relies on objective, reproducible observations, there is obviously a need to make agent-based models more accessible to readers and thereby increase the scientific credibility of the methodology (Law 2007). In order to address the communication problem, Grimm et al. (2006; 2010) propose a standard protocol to describe agent-based models with the primary purpose of making writing and reading model descriptions easier and more efficient.[71] Using a common format promotes a more rigorous and complete model description and thereby enhances transferability of knowledge between models. Furthermore, a familiar structure guides readers by way of common expectations and helps them to compare different models. To summarize, a standardized format for model description appears essential for increasing the accessibility and credibility of agent-based simulation (Deckert & Klein 2010).

The building blocks of the ODD (Overview, Design concepts, Details) protocol, which will determine the structure of chapter 5, are reported in Figure 4-3.[72]

[71] Grimm et al.'s ODD protocol (Overview, Design concepts, Details) was originally developed in the field of ecological modeling (Grimm et al. 2006). Since then, it has been used in more than 50 publications from diverse disciplines (Grimm et al. 2010) and is regarded as a standard toolkit for model description (Lorscheid et al. 2012).

[72] A short note on the 'overhead' of the ODD protocol: One critique of the ODD protocol is the problem of redundancy. For instance, the purpose of the model has already been described in the introduction of this dissertation. Nevertheless, as prescribed by the ODD protocol, it is also part of the overview paragraph (section 5.1.1). It is believed, though, that a certain degree of redundancy is unavoidable for a standardized model description when placed in a larger context. Furthermore, this critique applies to hierarchical structures in general and is the price to pay for reaping the benefits of a standardized format.

Figure 4-3 **Elements of the ODD protocol for model description**
(Source: Grimm et al. 2006, 2010)

Overview	Purpose
	Entities, state variables, and scales
	Process overview and scheduling
Design concepts	Design concepts
Details	Initialization
	Input data
	Submodels

In order to counter the criticism of simulation models as 'black boxes', both the simulation model and the experimental phase will be presented in a very detailed manner, allowing the reader to fully evaluate the work and to develop confidence in the results.

4.3.2 Phase 2: Model coding

The second phase, model coding, refers to the implementation of the conceptual model as a computer program. At this stage, the conceptual model is transformed into programming code. Model coding can be performed using either all-purpose programming languages or specially designed simulation toolkits for agent-based modeling (Macal & North 2010). An advantage over programming the model from scratch, simulation toolkits address the special requirements of agent-based modeling and simulation. They provide basic functionalities such as scheduling, methods for agent interaction, probability functions and data output methods. Making use of a simulation toolkit allows the researcher to focus on the programming of the agent logic and save development time. Today, there are more than 50 different toolkits available which provide functionality for the development of agent-based models. Some of the simulation environments are open source and provided free of charge, whereas others are available under a paid proprietary license. The existing toolkits vary heavily in their range of features, graphical interface, data output capabilities and documentation as well as community support, and rely on different programming languages (*Java*, *C*, *Phyton* and *Logo*, among others). Tesfatsion (2012) provides a comprehensive compilation of the available toolkits in the field of agent-based computational economics (ACE) and complex adaptive systems (CAS). Railsback et al. (2006) review five popular software platforms for scientific agent-based models (*NetLogo*, *MASON*, *Repast*, *Swarm Objective-C* and *Swarm Java*) by implementing example models in each of them. Crawford (2009) compares three toolkits (*NetLogo*, *Repast* and *AnyLogic*) and assesses their suitability for management and entrepreneurship research. Nikolai & Madey (2009) examine the full spectrum of agent-based modeling platforms and characterize the various toolkits according to five dimensions. As shown by their results, there is no one best choice among the toolkits; the level of suitability very much depends on the specific simulation task and the researcher's technical background.

In the model coding phase, v*erification* describes the process of ensuring that the conceptual model is accurately represented by the computer code. Does the computer model behave as it was planned to behave? Debugging is a crucial and ongoing process in any software project, but for simulation research in particular. A surprising relationship between two variables could either be due to a mistake in the model code, or it may be an extraordinary finding that had been previously overlooked, thus constituting a theoretical contribution. In order to prevent mistakes in the implementation process, various approaches are suggested in the literature (Gilbert & Troitzsch 2005, pp. 211-213; North & Macal 2007, pp. 221-226). Gilbert & Troitzsch (2005) propose debugging the model using a set of extreme test cases for which the simulation outcomes are easily predictable. As most simulation models incorporate elements of randomness, each simulation run is different, which complicates the verification process. In addition, extensive logging statements at the agent level can help to better understand the macro-level behavior of the model by analyzing the life cycles of individual agents, tracing their decision logics and internal states. Lastly, structured source code walkthroughs together with an experienced programmer are an effective tool for quality assurance (North & Macal 2007).

4.3.3 Phase 3: Design of experiments

Phase 3, the design of experiments, prepares the computational model for experimental usage (Wijermans 2011). The design of experiments (DoE) is defined as "the process of planning, designing and analyzing the experiment so that valid and objective conclusions can be drawn effectively and efficiently" (Antony 2003, p. 7). In this regard, *effectiveness* relates to ensuring the validity and reliability of the findings, whereas *efficiency* addresses the optimal experimental design to cope with resource constraints (Lorscheid et al. 2012).[73] Finally, a comprehensive design of experiments increases transparency of the subsequent model analysis process.

First of all, the input variables (factors) need to be specified, including their value range and factor levels. Likewise, the output variables (response variables) and their measurement levels are defined. An appropriate factorial design is to be selected in order to "analyze and quantify the effects of a large number of variables and detect possible interaction effects which easily go unnoticed by traditional sensitivity analyses" (Lorscheid et al. 2012, p. 27). In order to produce accurate, statistically significant results with stochastic models, the researcher has to decide on the run length of the simulation, i.e., the number of time steps, as well as the number of repetitions. As the model contains random elements, the results of just one simulation run cannot be relied on (Gilbert & Troitzsch 2005). Instead, the simulation will have to be run many times in order to observe its performance in a variety of conditions. Furthermore, the simulation model needs to be adapted so that the output data is stored in a structured and sufficiently detailed manner for further analysis.

Verification in this phase ensures that the experimental model stills works as expected and that the output format is free of errors.

4.3.4 Phase 4: Experimentation and data analysis

The fourth phase, experimentation and data analysis, refers to conducting the simulation experiments and analyzing the output data to generate new insights. For computer-based simulation, experimentation is described as searching the solution space, which denotes "the total range of conditions under which the model might be run" (Robinson 2004, p. 169).

Model execution typically takes place in two forms: interactive execution and batch execution (Macal & North 2010). Interactive execution typically includes a visual display which shows the agents, their properties and the graphical simulation environment. The researcher can watch the simulation run, control the speed of execution and even make changes to the model during run time that have an immediate effect. The visual representation helps to identify

73 Apart from a good introduction on design of experiments in simulation research by Lorscheid et al. (2012), see also Law (2007, pp. 619-668), Siebertz et al. (2010, pp. 151-158) and Kleijnen (2008).

potential problems and to gain a better understanding of the simulation (Robinson 2004). Subsequently, batch execution is used to actually generate the output data by repeatedly running the model for a defined set of conditions, as specified by the design of experiment in phase 3. Depending on the computing power of the machine, the complexity of the model, the number of factors, factor levels, model time steps and repetitions, batch execution can be heavy in terms of computing time.

After experimentation, the output data is examined with graphical and statistical methods. The aim is to uncover relationships among the variables, to quantify the observed dependencies and to detect possible interaction effects. Sensitivity analyses help to understand the extent to which the behavior of the system is sensitive to changes in other model inputs beyond the experimental factors (Robinson 2004). In this regard, sensitivity analyses are used to assess the robustness of the solution (Harrison et al. 2007). If it turns out that the output is highly sensitive to small variations in input parameters, extra care must be taken to ensure that the chosen values are accurate and reflect the target object (Gilbert & Troitzsch 2005).

The *verification* process during the experimentation phase ensures that all input variables (factors) are correctly set, as previously defined in the design of experiments.

4.3.5 Phase 5: Evaluation of results

Phase 5 deals with the evaluation of the simulation results to assess the *external validity* of the model. If the model appears to be valid, the understanding contributes to the "exploration, elaboration, and extension" of existing theory (Davis et al. 2007, p. 482).

To assess the validity, the findings derived from the model can be compared to the real-world phenomenon that was initially used for conceptual modeling. Do the results of the simulation match the empirical evidence? In order to enhance the scope of the findings, the derived theoretical relationships can be validated by new empirical research in other contexts and through deductive hypothesis testing (Garcia 2005). Likewise, Davis et al. (2007) suggest comparing the model outcome to either large-scale quantitative empirical data or case study data, depending on the source of theory embodied in the model.

In some cases, empirical data may not (yet) be available for comparison with the simulation results. In these situations, it is helpful to ask whether the identified causal relationships in the simulation model *make sense* for the target object and satisfy the criterion of theoretical plausibility (de Vaus 2003). However, while a generalization to other settings may be tempting, great care has to be taken not to overstress the simulation results without further empirical evidence (Harrison et al. 2007).

This process of comparing the simulation results with the real-world target and linking them to new and existing theory can lead to a redefinition of the conceptual and computational model, thus necessitating new simulation runs to improve the explanatory power of the model. This highlights the role of simulation research as part of an iterative scientific process, as illustrated in Figure 4-2.

In this chapter, I discussed the suitability of various quantitative and qualitative methods for answering the research question. I explained the rationale for selecting an agent-based simulation approach and put forward a phase model of simulation research. The different phases are reflected in the structure of the dissertation. Chapter 5 focuses on the modeling stage and outlines the conceptual model of path dependence in two-sided markets, followed by a formal description that provides the basis for the implementation of the computational model. Chapter 6 presents the empirical case, which is then used for model validation and calibration in chapter 7. Chapter 8 addresses the design of experiments as well as the experimentation and data analysis. Chapter 9 concludes by discussing the theoretical implications of the simulation results as well as the practical implications.

5 Model

The present chapter outlines the conceptual model for exploring the conditions for path dependence in two-sided markets. The theoretical foundations of technological path dependence and two-sided markets have been thoroughly discussed in chapter 2 and provide the context for the model design. The agent-based simulation model is an adapted and advanced version of Sterman's system dynamics model of a two-sided market (Sterman 2004, p. 371), which was already outlined in section 4.2. Furthermore, the simulation model draws on contributions by Gupta et al. (1999), Buxmann (2001), Gandal (2002) and Zhu & Iansiti (2012).

The model structure follows the classic "hardware/software paradigm" (Katz & Shapiro 1985) that applies to many technology markets with indirect network effects, such as the markets for personal computers, smartphones, video game consoles or audio and video equipment (Katz & Shapiro 1994; Gupta et al. 1999; Church et al. 2008). Table 5-1 shows possible applications of the generic model, which will be referred to in the subsequent model description to foster a better understanding. 'Stylized facts' drawn from these empirical examples provide guidance for model building. Please note that the list of possible applications is not meant to be exhaustive. As can be seen, the generic model is intended to be applicable to a collection of related industries which exhibit platform competition in two-sided markets with indirect network effects. Among these examples, the smartphone industry deserves special attention as this empirical application will later be used to calibrate the simulation model in chapter 7.

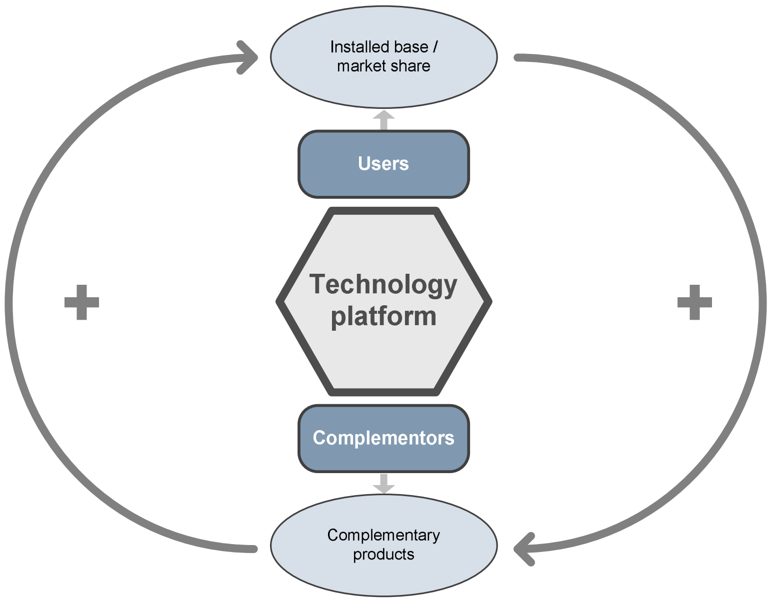
Table 5-1 Possible applications of the model

Industry	*Platform*	*Side 1 (Complementors)*	*Side 2 (Users)*
Personal computers	PC operating systems (*Microsoft Windows, Apple MacOS, Linux*)	Software developers, programming software for PCs	Users, choosing a PC system
Video tapes	Analog video formats (*VHS, Betamax*)	Movie studios, releasing prerecorded video tapes	Users, choosing a home video system
Home video games	Video game consoles (*Nintendo Wii, Microsoft Xbox, Sony PlayStation*)	Game developers, developing home video games	Users, choosing a console hardware
Video discs	Digital video formats (*Blu-ray, HD-DVD*)	Movie studios, releasing prerecorded video discs	Users, choosing a home video system
Smartphones	Smartphone operating systems (*Google android, Apple iOS, Symbian*)	App developers, programming software for smartphones	Users, choosing a smartphone device

Prior to describing the model, I provide a short refresher on the two-sided market concept. All of the model applications in the list above can be described by a stylized representation of a two-sided market with positive indirect network effects due to complementary products, which is shown in Figure 5-1.[74]

[74] The self-reinforcing nature of indirect network effects is also shown in Figure 2-3.

Figure 5-1 **Two-sided market with positive indirect network effects**



In the depicted two-sided market context, two groups of agents ('users' and 'complementors') interact through an intermediary ('technology platform'). Referring to the previous example, the operating systems of PCs or smartphones provide a common *software platform* for application developers and users. Likewise, video formats such as *VHS*, *DVD* or *Blu-ray* act as an intermediary between content publishers, such as movie studios, and consumers. Furthermore, in a two-sided market there is some interdependence between both groups of actors: the utility of one group's members depends on the size of the other group and vice versa. In the hardware/software paradigm, users benefit from a large group of complementors which provide complementary products for the platform. For example, *Windows* users can choose from a large variety of compatible software, *PlayStation* owners enjoy a large range of games for their console and movie enthusiasts benefit from a large number of available *Blu-ray* titles. Changing perspective, complementors benefit from a large group of users, as it makes the provision of complementary products for that platform more attractive. For instance, the development of a smartphone app for the *Apple iPhone* becomes more profitable if there are millions of *iPhone* owners that form the potential customer base. Movie studios are much more willing to release pre-recorded *Blu-ray* discs when *Blu-ray* players have reached widespread adoption.

Putting these two effects together reveals the logic of increasing returns which is inherent to the system depicted in Figure 5-1: more users make a platform more attractive to complementors; these complementors provide more complementary products, which in turn make a platform more attractive to users. In other words, success breeds success. For instance, an increase in the number of *iPhone* users increases the demand for *iPhone* apps and hence the number of developers for the *iPhone*. As a result of the higher variety of apps, the *iPhone* platform becomes more valuable to existing and potential *iPhone* users, the platform's market share grows further. In this sense, both users and complementors make up a 'virtual' network (Katz & Shapiro 1994) where the utility for each group's members increases with the growth of the virtual network. This effect is called an indirect, or virtual, network effect (Gandal 2002), since the platform's value for a user depends *indirectly* on the number of other users of that platform. This stylized illustration of a two-sided market setting sets the scene for a thorough understanding of the proposed simulation model.

The model description follows the ODD (Overview, Design concepts, Details) protocol (Grimm et al. 2006, 2010).[75] The model description is structured as follows. First, a general overview is provided with a summary of the overall objectives for which the model was developed. I explain which agent types are part of the model and how these agents behave in the model environment over time. Second, general concepts and simulation approaches underlying the model design are outlined, such as adaptation, interaction and stochasticity. Third, additional 'technical' details regarding the model parameters and the agents' behavior are provided for readers interested in an in-depth discussion of all aspects of the simulation model.

5.1 Overview

The present section provides a summary of the overall purpose and structure of the model, with a verbal description of the incorporated agents, their properties and behaviors as well as the model environment. The objective for this overview section is to keep the model description at a conceptual, verbal level. It forms the basis for a formal description of the model's equations, rules and algorithms in section 5.3.

[75] The ODD protocol is an attempt to provide a common format in order to enhance transferability of knowledge between simulation models. See section 4.3.1 for more information.

5.1.1 Purpose

The purpose of the model is to explore the conditions for technological path dependence in two-sided markets in order to better understand how and why network industries can tip towards inferior technology platforms. The model highlights the interplay between the diffusion/adoption of innovation and firm strategies in an emerging industry. It identifies favorable and unfavorable aspects for the emergence of technological lock-ins by analyzing the long-term impact of small events in the early phase of industry evolution under the influence of indirect network effects. The generic model contributes to the theoretical literature on path dependence by complementing existing empirical case studies with a formal simulation model.

5.1.2 Entities, state variables and scales

In this section, I outline the conceptual model by elaborating on the incorporated agents (‘entities’), their behavioral attributes and model parameters (‘state variables’) as well as the model’s spatial and temporal scales.

The model incorporates three main entities: (1) competing platforms, (2) users and (3) complementors. Each platform is associated with a group of (end) users and a group of complementors that provide complementary products for the platform. The competing platforms vary in quality and enter the market either simultaneously or successively.

The model represents an emerging industry formed by a technological innovation. Therefore, users first need to adopt the innovation before choosing a certain platform. The innovation adoption process is described by means of the classic Bass diffusion model. Users are embedded in a scale-free network of social relations where innovation adoption is triggered by social interaction as well as external stimuli. During innovation adoption, users engage in an information search to form a consideration set of platform alternatives. Because of imperfect information, users may be unable to evaluate all platforms. Users rely on external sources as well as interpersonal sources for their information search. Hence, users utilize the competence of other agents and consider recommendations of users in their social network. After innovation adoption and the information search on platform alternatives, users engage in decision-making. For this purpose, they evaluate the platforms in their consideration set using a compensatory multi-attribute model in which a negative evaluation of one attribute can be compensated for by positive evaluations of others. Users assess technology platforms on two dimensions: (1) the *inherent value*, or 'quality', of the platform, and (2) the *network value* from the availability of complementary products. Users prefer platforms of good quality and with many complementary products available. However, they act in a boundedly rational manner and cannot perfectly assess the quality of the technology platforms. Hence, their evaluation is biased by a stochastic quality perception variance.

Complementors provide complementary products for either one or multiple technology platforms. All platforms are incompatible with each other; thus complementary products are developed specifically for one platform and cannot be used with others. Complementors gradually enter the emerging industry as the provision of complementary products becomes more attractive as the result of more users adopting the innovation. Complementors aim to maximize 'reach' (a proxy for sales potential), and thus prefer to develop complementary products for platforms with a large user base. They allocate their development resources either to one technology platform ('single-homing') or multiple platforms ('multi-homing'). Accordingly, there is a trade-off between lower market coverage in the case of single-homing and additional development effort in the case of multi-homing. Complementors decide on their platform strategy according to the platforms' market share and the level of development synergies between the platforms.

Both users and complementors are able to switch to other technology platforms over time. However, frictions and resource constraints prevent instant switching. Thus, both users and complementors are bound to their platform choice for a certain decision-horizon period.

Figure 5-2 provides a bird's-eye view of the generic model and highlights the system's positive feedback loop[76] resulting from the interdependent decisions of users and complementors. All variables as well as the underlying assumptions will be explained in full detail in the following paragraphs.

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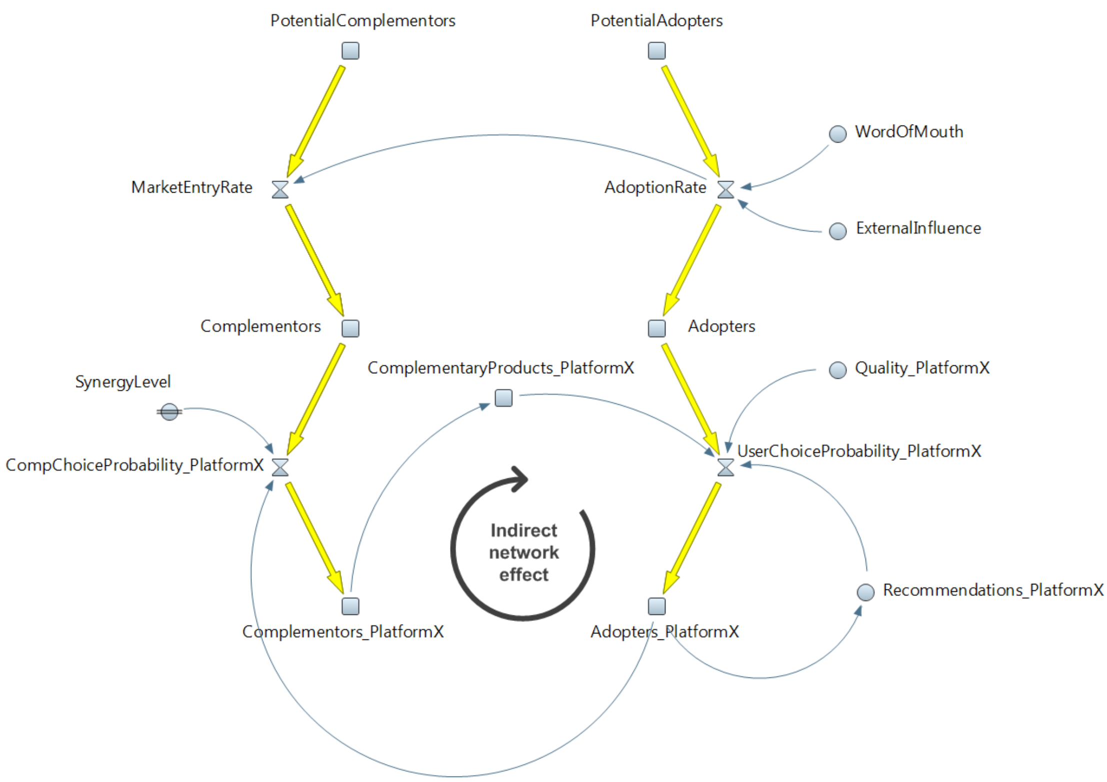
[76] Pursuing a bottom-up approach, it should be stressed that the agent-based simulation model does not directly specify the feedback loops at the system level. Nevertheless, the system dynamics *notation* used in the causal loop diagram is believed helpful to communicate the macro-level behavior of the agent-based model as a whole.

Figure 5-2 **Simplified model overview**



The right-hand side of the illustration explains users' choice of technology platform. The initial adoption of the innovation is triggered by word of mouth or by an external influence. The probability that a user then chooses a certain technology platform, for instance platform X, is determined by the (exogenous) quality of the platform, the (endogenous) number of complementary products for this platform and the (endogenous) recommendations of other users. The interdependent decision of the complementors is shown on the left-hand side of the figure. Complementors enter the emerging industry gradually. The probability that a complementor then chooses a certain technology platform is influenced by the (endogenous) market share of the platform and the (exogenous) synergy level for multi-platform development.

An integrated perspective of both decision logics shows the positive feedback loop resulting from the indirect, or 'virtual', network effect in this two-sided market setting. A large number of complementary products increase the likelihood that a platform is chosen by users, causing the platform's market share to rise. In turn, this higher market share increases the likelihood that the platform is supported by complementors, causing the number of complementary products for the platform to rise. The positive feedback loop is thus complete.

After this general description of the model, the entities are explained in more detail in the following sections, including references to the theoretical foundations of the model design. Where applicable, alternative approaches to modeling are outlined and the advantages of the chosen approach are discussed.

5.1.2.1 Platforms

The model describes an industry with an arbitrary number of rival technology platforms that compete for control of the market.[77] Each platform is associated with a group of end users and a group of complementors that provide complementary products for the platform. Complementary products are developed specifically for one platform and cannot be used with others. For example, software applications for the *Apple Mac* cannot be used on *Windows* PCs, and *VHS* cassettes cannot be played on *Betamax* machines.

It is assumed that the competing platforms vary in quality, which is reflected in their *inherent value* to users in the absence of any complementary products.[78] A platform's quality is defined as a composite of attributes (Tellis et al. 2009). For instance, the quality of a smartphone software platform depends on its performance, the usability of the graphical user interface, built-in functionality (e.g., internet browser, calendar) as well as a user-friendly implementation of the core phone features such as making phone calls or using the camera. For video formats such as *VHS* and *Betamax*, the quality of the technology is determined by picture quality and recording time (Cusumano et al. 1992). In the present model, the platform quality is numerically expressed by an objective quality index, similar to the approach by Tellis et al. (2009). In line with other models on platform competition (Zhu & Iansiti 2012), it is assumed that the quality is constant over the platform's life cycle, so there is no possibility for technological development after the platform's market entry.

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[77] Most related models assume a simpler setup with only two technological options. For instance, in Arthur's classic model of technological path dependence, two technologies A and B compete for adoption (Arthur 1989). Likewise, Zhu & Iansiti (2012) model the competition between one incumbent and one entrant platform. Although such an approach would be much easier to implement, it is believed that a model with an arbitrary number of competing platforms is much closer to reality and enhances the external validity of the model.

[78] The inherent value is also termed "stand-alone benefit" by Gandal (2002).

The platforms enter the market either simultaneously or successively. In case of successive market entry, it is assumed that the quality of the entering platforms increases over time; i.e., new entrants possess better quality than incumbent platforms. This is a reasonable assumption especially for technology markets, given that late entrants benefit from longer development times and can imitate the functionality of successful incumbent platforms.

The class diagram below shows the state variables and methods of a platform object.

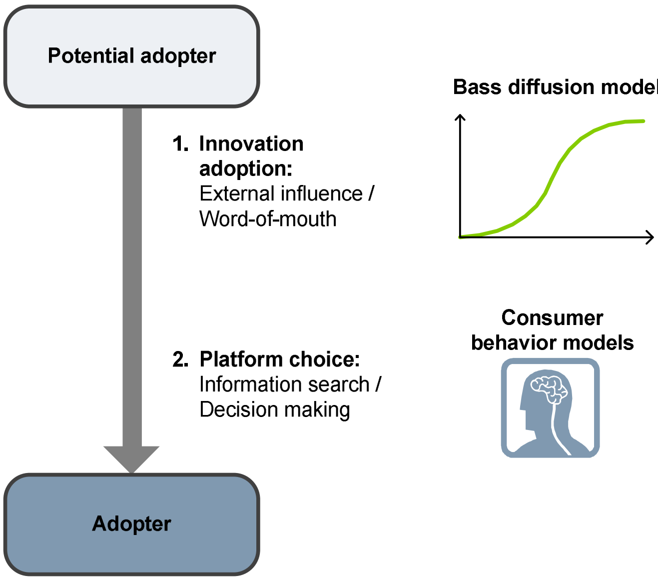
Figure 5-3 **Platform class diagram**

Platform
State variables - ID : String (const) - Quality : double (const) - Time of market entry : double - Number of complementary products : int
Methods - enterMarket ()

5.1.2.2 Users

The model represents an emerging industry formed by a technological innovation. Therefore, users first need to adopt the innovation before choosing a certain platform. For instance, users first become convinced of the benefits of a home video system prior to making a decision for *VHS* or *Betamax*. Figure 5-4 illustrates the two-step process of innovation adoption and platform choice.

Figure 5-4 Innovation adoption and platform choice: a two-step process



For the innovation adoption (step 1), the simulation model draws on the classic Bass diffusion model.[79] *Potential adopters* are influenced by external stimuli as well as by word of mouth from *adopters*. For the platform choice (step 2), the model relies on theories of bounded rationality and insights from consumer behavior theory on how users search for and process information, and subsequently make decisions.

5.1.2.2.1 Innovation adoption

An innovation is defined as "an idea, practice, or object that is perceived as new by an individual or other unit of adoption" (Rogers 2003, p. 12). The success of an innovation depends on its acceptance by consumers. Cumulative sales of an innovative durable product, such as PCs, smartphones or video recorders, generally follow an S-shaped curve, a concept introduced in the 1960s and first supported by empirical evidence by Bass (1969).[80] The Bass diffusion model remains one of the most common methods to explain and predict innovation adoption at an

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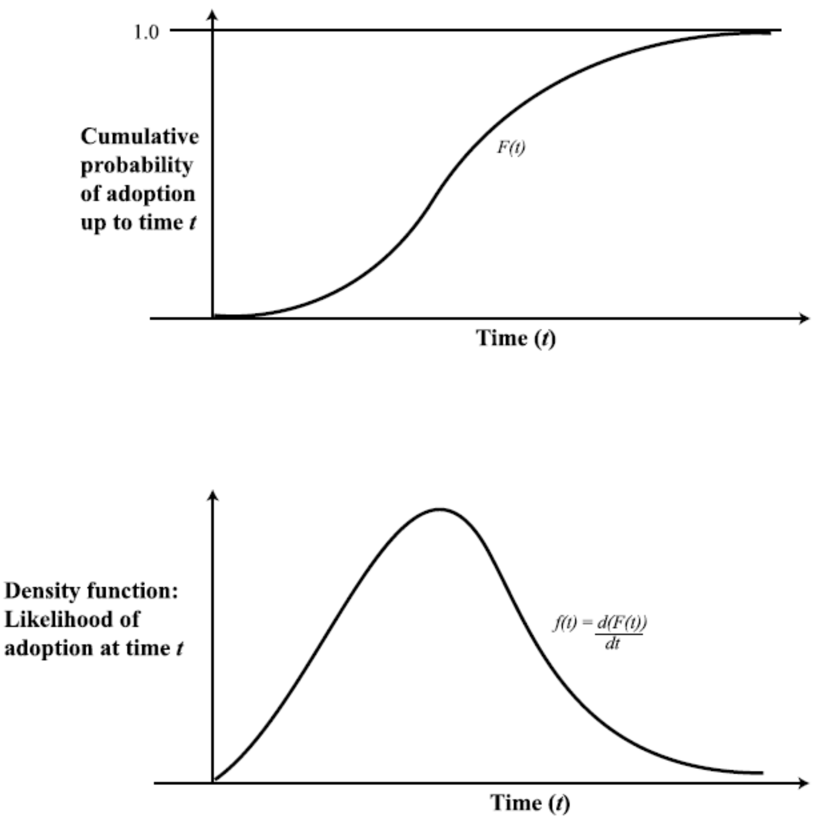
[79] Other diffusion models could alternatively be employed. See Meade & Islam (1998) for a review and classification of 29 diffusion models for technological forecasting. See also Weiber (1992), who proposes a diffusion model for critical mass systems in telecommunications.

[80] The presentation of the Bass model builds on Bass' original paper (1969), Rogers (2003) and Lilien & Rangaswamy (2004).

aggregate level (Bass 2004).[81] It assumes a population consisting of innovators and imitators. When a technological innovation becomes available on the market, the innovators purchase it first because of external stimuli such as advertising. These early adopters influence the imitators to adopt the innovation as well using word of mouth. The combined effect is an S-shaped diffusion pattern with a slow diffusion start, followed by rapid growth and a final saturation phase (see Figure 5-5).

Figure 5-5 **Bass diffusion model: probability of innovation adoption over time**
(Source: Lilien & Rangaswamy 2004)



The S-shaped diffusion curve is described by the following differential equation, first proposed by Bass (1969):

81 In fact, in 2004 the original paper by Bass (1969) was voted one of the "Top 10 Most Influential Papers" published in the 50-year history of *Management Science*.

$$\frac{f(t)}{1 - F(t)} = p + \frac{q}{M} A(t)$$

where

t	=	time interval, typically expressed in years,
$f(t)$	=	the fraction of the potential market that adopts exactly at time t,
$F(t)$	=	the fraction of the potential market that has adopted up to and including time t,
p	=	the Bass model coefficient of innovation (external influence),
q	=	the Bass model coefficient of imitation (word of mouth),
M	=	a parameter representing the size of the potential market,
$A(t)$	=	the cumulative number of adopters up to and including time t.

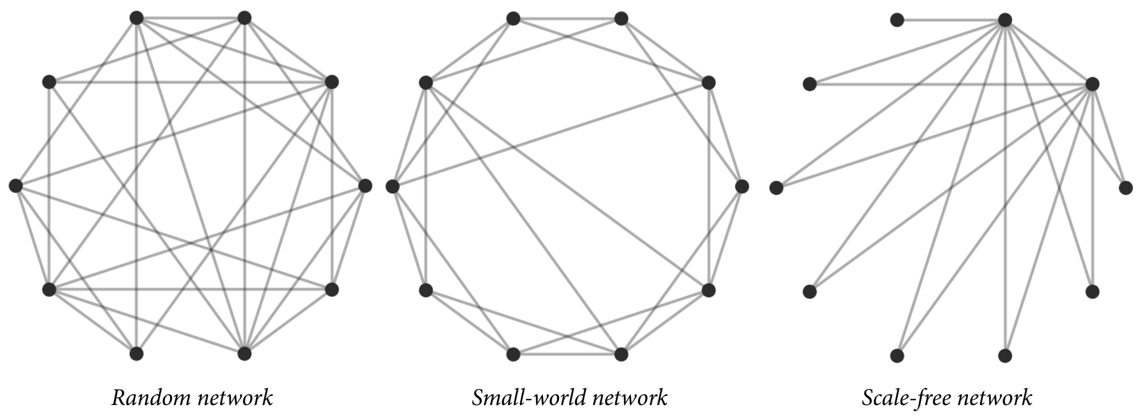
The fraction of potential adopters that adopt at time t (from the set of users that have not yet adopted) is equal to a linear function of the coefficients p and q as well as the cumulative number of previous adopters. The equation reveals the logic behind the two adoption triggers of the Bass model. The effect of the external influence coefficient p is independent of how many consumers have already adopted the innovation before time t. In contrast, the effect of the word-of-mouth coefficient q is proportional to the number of adopters by time t, representing the extent of favorable interactions (Lilien & Rangaswamy 2004).

In the simulation model, the diffusion/adoption process is modeled explicitly at the individual level. Therefore, the underlying logic of the Bass model in its differential-equation form is carried over into an agent-based approach. The simulation model incorporates an external effect that causes a fixed fraction of the potential adopters to adopt the innovation at each period of time. Furthermore, potential adopters come into contact with adopters through social interaction, modeled by means of an interpersonal network. This word-of-mouth effect also induces the adoption of the innovation. As a consequence of the word-of-mouth mechanism, the network topology has a crucial impact on the diffusion process (Watts & Strogatz 1998; Rogers 2003; Hein et al. 2006; Rahmandad & Sterman 2008). Three major network topologies can be distinguished:

1. *Random networks* (Erdos & Renyi 1960), also referred to as ER models: all nodes are randomly connected;
2. *Small-world networks* (Watts & Strogatz 1998): these lack highly connected hubs and are characterized by some long-range links;
3. *Scale-free networks* (Barabási & Albert 1999): most nodes have few links, whereas some hub-nodes are hyper-connected.

Figure 5-6 below illustrates the three alternative network topologies.

Figure 5-6 **Comparison of different network topologies**
Random, small-world and scale-free; each network topology is based on ten nodes.



As three viable alternatives exist, a decision had to be made regarding which network structure should be used to realistically model social influence in the simulation model. Since "network structure is typically invisible" (Dover et al. 2012), for a long time there was an "absence of clear empirical evidence regarding the structure of influence networks" (Watts & Dodds 2007, p. 443) due to lack of large-scale empirical data. However, a recent paper by Goldenberg et al. (2009) based on data from an online social network provides compelling empirical evidence that the scale-free structure is the most realistic assumption for influence networks. This belief is backed by Dover et al. (2012), who develop a novel statistical approach to uncover the network topology based on diffusion data. They apply their method to various real-world diffusion processes and find that the scale-free structure is indeed the most common network type. Based on these arguments, the simulation model incorporates a scale-free network topology instead of a random ER model (Erdos & Renyi 1960) or a small-world network (Watts & Strogatz 1998). The distribution of the number of links per person, termed 'degree', follows a power law: some nodes are hyper-connected, whereas the majority have only few connections (Goldenberg et al. 2009).

In summary, the diffusion of innovation is modeled at the individual level. Agents are embedded in a scale-free network of social relations. Innovation adoption is triggered by word of mouth and by external stimuli.

5.1.2.2.2 Information search

Once users are convinced of the benefits of the innovation and adoption has taken place, they need to decide on a particular platform. The process of platform choice is separated into (1) the *information search* phase, where users seek information on platform alternatives, and (2) the *decision-making* phase (Kardes 2002; Hoyer & MacInnis 2004). For both stages, the model assumes boundedly rational actors (Simon 1955), which allows for a more realistic model of decision processes compared to traditional approaches built on the notion of perfect rationality. The term 'bounded rationality' refers to "rational choice that takes into account the cognitive limitations of the decision-maker — limitations of both knowledge and computational capacity" (Simon 1997, p. 291). Various approaches have been proposed to model bounded rationality (Arthur 1994c; Simon 1997; Rubinstein 1998; Epstein 2006). For the agent-based model, I separately address both *limitations of knowledge* and *limitations of computational capacity* (Epstein 2006). Limitations of knowledge play a role in the information search stage, whereas limitations of computational capacity are important in the subsequent decision-making stage.

In the information search phase, limitations of knowledge are represented by means of a *consideration set*. Dating back to Simon (1955), the consideration set is a "subset of behavior alternatives that the organism 'considers' or 'perceives'" so that "the organism may make its choice within a set of alternatives more limited than the whole range objectively available to it" (Simon 1955, p. 102). The concept has been widely adopted in consumer behavior research (Hoyer & MacInnis 2004). In the present model, the size of the consideration set is limited according to information processing constraints. Hence, users may be unable to evaluate the whole range of platforms available in the marketplace. Users first identify a subset of platforms for further evaluation (i.e., the consideration set) and then choose from this limited set of alternatives (Kardes 2002; Hauser 2011).

Consumer behavior theory argues that information search occurs either internally from memory or externally from outside sources (Hoyer & MacInnis 2004). As the current model represents an emerging market, it is assumed here that users have no preferred brands, attributes, evaluations or experiences in memory that they can call on. Thus, they focus completely on an external search, such as advice from trusted friends or relatives, recommendations from dealers or information from magazines, the internet or advertisements. For modeling purposes, the various sources for external information are combined into two channels: (a) interpersonal sources and (b) other external sources.

In the model, these concepts are applied as follows. When users search for information on platform alternatives, they first seek advice from other adopters in their social network.[82] Adopters recommend the platform they have already chosen, i.e., there is no negative word of mouth incorporated in the model. Users only communicate with agents to whom they are directly connected and then include the recommended platforms in their consideration sets. One of the benefits of this modeling approach is that, as in reality, platforms with a large market share are more well-known and have a higher probability to be included in the consideration set. Apart from interpersonal sources, users also rely on other external sources for their information search, modeled as a random influence. As a result, their consideration set contains recommendations from their social network as well as a random selection of other platforms.

To summarize, agents have limitations of knowledge and may be unable to evaluate the entire range of platforms available in the marketplace. They rely on interpersonal as well as other external sources for the information search.

5.1.2.2.3 Decision-making

For their platform choice, users evaluate the technology platforms in their consideration set and form a decision. Various cognitive choice models can be used to describe this "high-effort thought-based decision-making" (Hoyer & MacInnis 2004; see also Kardes 2002). In this case, a compensatory multi-attribute model is used where a negative evaluation of one attribute can be compensated for by positive evaluations of others.[83]

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82 In fact, Bughin et al. (2010) provide evidence that consumer-to-consumer communication is one of the most important factors that influences the purchasing decision for technology products.

83 This is the standard way of modeling consumer choice in the light of quality differences and indirect network effects.

Similar to the approach by Gupta et al. (1999), the present model assumes that users evaluate technology platforms on two dimensions: (1) the *inherent value*, or 'quality', of the platform, and (2) the *network value* from the availability of complementary products. Users prefer platforms of good quality and which have many complementary products available. The inherent value is determined by the quality of a platform and has been already described in section 5.1.2.1. The network value of a platform depends on the variety and quality of complementary products. For the sake of simplicity, quality differences between complementary products for different platforms are not considered in the model.[84] Hence, ceteris paribus, platforms with a larger number of complementary products are preferred. It is assumed that the marginal benefit of an increase in the number of complementary products is of a diminishing nature. For instance, the rise from 0 to 1,000 complementary products for a technology platform is more highly valued than the rise from 10,000 to 11,000. This assumption is consistent with empirical evidence by Boudreau (2011) regarding complementary applications in the mobile computing industry, as well as a study by Ohasha (2003) for the VCR market. Accordingly, users' utility from the availability of complementary products is expressed by a *concave* utility function (Lilien et al. 1992).

The compensatory multi-attribute model additively combines the inherent value and the network value. Users choose the technology platform that yields the highest aggregate utility.[85] In this regard, a qualitatively inferior platform with a large number of complementary products can be more useful than a superior platform with few complementary products. For instance, the widespread *VHS* video system, with its many pre-recorded tapes available for sale and rental, was preferred over a technically superior *Betamax* recorder (Cusumano et al. 1992).

The model assumes boundedly rational actors with limitations of knowledge and computational capacity (Simon 1955). In the decision-making phase, limitations of

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84 In this respect, the model resembles the models by Gandal (2002) and Zhu & Iansiti (2012). It is believed that quality differences balance out in the portfolio of a platform. For instance, it can be reasonably assumed that movies available on *VHS* are not generally better (i.e., have more prominent actors or a more creative plot) than movies available on *Betamax*.

85 Alternatively, logit and probit discrete choice models could be used (see for instance Lilien & Rangaswamy 2004). However, the incorporated additive model is a prerequisite for the empirical calibration of the decision-making process using a conjoint analysis, which is described in chapter 7.

computational capacity come into play. Users are unable to perfectly assess and compare the quality of the different platforms in their consideration set; instead, their evaluation is biased by a stochastic quality perception variance which may lead to non-optimal decisions.

To summarize, users maximize utility by choosing the technology platform with the highest aggregate benefit based on quality and the number of complementary products, but under the constraints of imperfect information and limited cognitive abilities.

5.1.2.2.4 Switching

After their initial platform choice, users may cease to use a platform and switch to an alternative, either to correct 'wrong' decisions or because an incumbent platform with superior quality has entered the market since their initial choice. However, inertial forces may hinder switching to another platform. These so-called *switching costs* are central to information technology industries (Farrell & Klemperer 2007). In platform-based markets with complementary products, switching costs can take various forms. With PC operating systems, for instance, users face the costs of learning, installing, and maintaining the new operating system when switching to another system (Economides & Katsamakas 2006). Furthermore, users may lose compatibility with other users with respect to exchanging files. Even more importantly, their purchased software applications are generally incompatible with the new operating system. Shapiro & Varian (1999, p. 12) conclude: "Switching from Apple to Intel equipment involves not only new hardware but new software. … The switching costs for changing computer systems can be astronomical." In the example of home video systems, users lose their collection of *VHS* video tapes when switching to a *Betamax* machine.

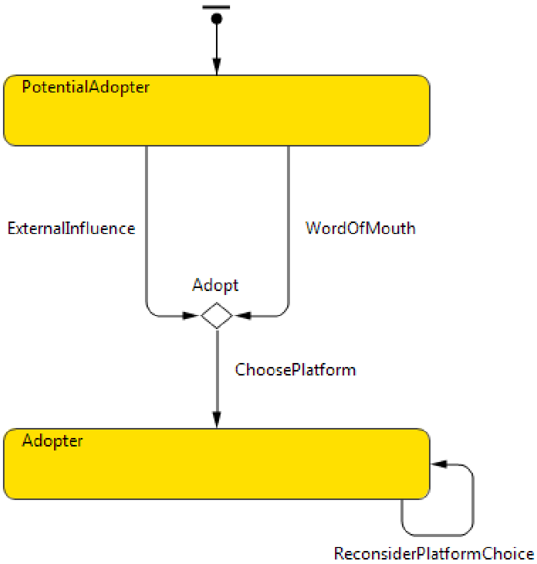
In the model, the various forms of switching costs are combined into a single measure, the 'decision horizon' (Lewis 2005; Ebert 1976). Users are bound to their platform choice for a given period of time before they reconsider their platform choice. Accordingly, as the model omits any pricing, the ease of switching is expressed in time units. This approximation is a reasonable assumption because the value of complementary products decays over time. When users place high value on their existing collection of complementary products, switching costs are high and users stick to their chosen platform for a long period. Accordingly, high switching costs, of any form, are associated with a long decision horizon, while low switching costs are associated with a short decision horizon. At its maximum value, the decision horizon equals the total model runtime. In this case, switching is impossible and users are bound to their initial choice forever. In the marginal case of a decision horizon of zero, users instantly reconsider their platform choice.

5.1.2.2.5 Summary: Class diagram and state chart

Figure 5-7 shows the class diagram and the state chart to describe the state variables, methods and life cycle of a user agent. More details are provided in section 5.3.3.2.

Figure 5-7 **User class diagram and state chart**

User
State variables - ID : String (const) - Bass external influence : double (const) - Bass word-of-mouth : double (const) - Information level : double (const) - Rationality level : double (const) - Network utility limit : double (const) - Network utility gradient : double (const) - Decision horizon : double (const) - Platform : Platform
Methods - adopt() - choosePlatform () - reconsiderPlatformChoice () - receiveMessage (message, sender) - sendMessage (message, receiver)



5.1.2.3 Complementors

The present model assumes a fixed number of complementors (Gupta et al. 1999; Farrell & Klemperer 2007), also termed 'content providers' or 'content developers', who provide complementary products for either one or multiple technology platforms. For instance, software developers program third-party software applications for *Windows* and/or *Linux*. Likewise, film studios publish pre-recorded video tapes/discs for rental or sale for specific video format such as *VHS* or *Betamax*, and *HD-DVD* or *Blu-ray*. The competing platforms are incompatible with each other, so that complementary products developed specifically for one platform cannot be used with others.

5.1.2.3.1 Market entry

Complementors gradually enter the emerging industry as the provision of complementary products becomes more attractive as the result of more users adopting the innovation. Therefore, an increase in the installed base of users induces more complementors to enter the market.[86] For instance, the number of software developers increases when personal computers became more popular. On average, complementors enter the market earlier than users because they recognize the importance of the innovation at an earlier stage. Thus, complementors lead the market and users follow. To account for this, the model assumes an adoption rate of complementors that is higher than the adoption rate of users.

5.1.2.3.2 Single- vs. multi-homing strategies: The effect of synergies

Complementors devote their resources, measured in model time steps, to supply complementary products for one or multiple technology platforms. Because the development effort is fixed and thus independent of the number of users, complementors prefer to provide complementary products for platforms with a large base of users.[87] Hence, complementors aim to maximize *reach* for their complementary products:

$$\text{Reach} = \text{potential user base} \times \begin{bmatrix} \text{total number of complementary products} \\ \text{developed in a given time period} \end{bmatrix}$$

Reach is a measure that is determined by the number of complementary products developed in a given time period and the total number of users who are able to buy and use these complementary products. Thus, reach serves as a proxy for sales potential. Under the assumption that sales opportunities, pricing and development cost (all outside the scope of this model) are independent of the platform, maximizing reach is the profit-maximizing strategy. In that sense, the model incorporates an adapted version of the standard profit maximization assumption as the objective for complementors.[88]

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[86] This assumption is also included in the model by Zhu & Iansiti (2012)

[87] This is the standard assumption for software products (Corts & Lederman 2009) and also applies to other intangible products with almost no marginal cost, such as movies.

[88] In other the words, the model assumes that output maximization leads to revenue maximization and ultimately to profit maximization. Adams & Juleff (2003, pp. 71-102) discuss the relationship between these different business objectives in more detail.

Complementors can allocate their development resources either to one platform or to multiple platforms. For example, they can spend 100 percent of their resources to specialize on one platform ('single-homing'), or they can split their resources to support multiple platforms ('multi-homing'). For instance, software developers can either develop applications solely for the *Windows* platform, or 'port' their *Windows* programs to the *Mac* platform as well (Farrell & Klemperer 2007, p. 2010). Likewise, movie studios can release titles exclusively on *Blu-ray*, or on both *Blu-ray* and *HD-DVD*. On the one hand, supporting multiple platforms is beneficial for firms because it increases the potential customer base for their complementary products, resulting in greater reach. On the other hand, multi-homing is associated with higher development effort when supporting multiple platforms. Obviously, complementors must engage in a trade-off between lower market coverage when single-homing and additional development effort when multi-homing.[89]

Depending on the 'degree of compatibility' between platforms[90], complementors may benefit from synergies when the same complementary product is developed for multiple technology platforms. In this case, the development of the same product for two platforms requires *less than twice* as many resources as the development for a single platform. For instance, video game developers can re-use some parts of the programming code and graphics when they port an application to another video console platform (Corts & Lederman 2009). Similarly, audio and video content can be released in different formats with little additional effort.

In the present model, the synergy level is measured as the fraction of development resources which produce output that can be simultaneously used for multi-platform development. For example, a synergy level of 0.5 implies that 50 percent of the development resources are beneficial for the focal platform and at the same time for all other supported platforms. In practice, the synergy level depends on the degree of compatibility between platforms. A high synergy level means it is rather effortless to support multiple platforms, whereas a low synergy level renders it inefficient.

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89 This means that the decision of how many technology platforms to support is determined on the basis of a cost-benefit analysis. This model design appears more realistic compared to a simpler approach with strict capacity constraints.

90 Wang et al. (2010) further distinguish between cross-generation product compatibility and within-generation product compatibility. See also Shy (2011) for a recent literature review on 'partial compatibility'.

When deciding on their platform strategy, complementors balance the additional effort for supporting multiple platforms with the gain in market coverage. Therefore, their decision on whether it pays off to support a certain platform depends on the market share of the respective platform and the level of synergies for multi-homing.

5.1.2.3.3 Decision basis

As argued above, the complementors' platform choice depends on the market shares of the competing platforms and the synergy level for multi-platform development. However, the term market share is ambiguous: what exactly is a platform's share of the market and how can it be determined? Market share commonly refers to the percentage of total *sales* over a specific *period of time*. However, a more accurate way for complementors to assess a platform's market share is to look at its installed base, i.e., the total number of units currently in *use*, which is a measure of a platform's network size. For durable goods, (short-term) market share figures fluctuate much more than installed base metrics and can give a misleading view of the market. On the other hand, short-term market share data gives an early indication of changing market trends.

The present model assumes that complementors, as opposed to user agents, have perfect information and are perfectly rational. Complementors form their platform decision based on installed base metrics which are freely available for all platforms.[91] In practice, a number of professional research and consulting firms provide detailed information on technology markets, including market share data. Furthermore, complementor firms spend extensive amounts of time and managerial resources on the platform decision. Accordingly, it is believed that the assumption of fully informed and perfectly rational actors is plausible here.

5.1.2.3.4 Switching

It is assumed that complementors are able to switch platforms. They are not necessarily doomed if it turns out that they 'bet on the wrong horse' and their supported platforms have lost significant market share. For instance, in early 2008 the movie studio *Time Warner* announced that they were abandoning the *HD-DVD* standard and would release new titles on *Blu-ray*

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91 Earlier versions of the model allowed complementors to either look at market share data or alternatively at installed base metrics. The simulation results were almost identical and the model was thus simplified.

instead. Accordingly, complementor agents revise their platform strategy if necessary depending on recent changes in platforms' market shares.

Empirical evidence suggests that the platform strategy is of utmost importance for complementors. However, adapting their platform strategy to new market realities is not an instantaneous process. In practice, friction and delays hinder a switch of platforms. Platform-specific resources, such as human knowledge or physical equipment, represent switching costs that continual permanent 'platform hopping'. For instance, "software houses that initially specialized in writing software for Apple computers learned all too soon that they needed to retool and thus bear very real switching costs: they had to become adept at writing programs to run on DOS or Windows" (Shapiro & Varian 1999, p. 131).

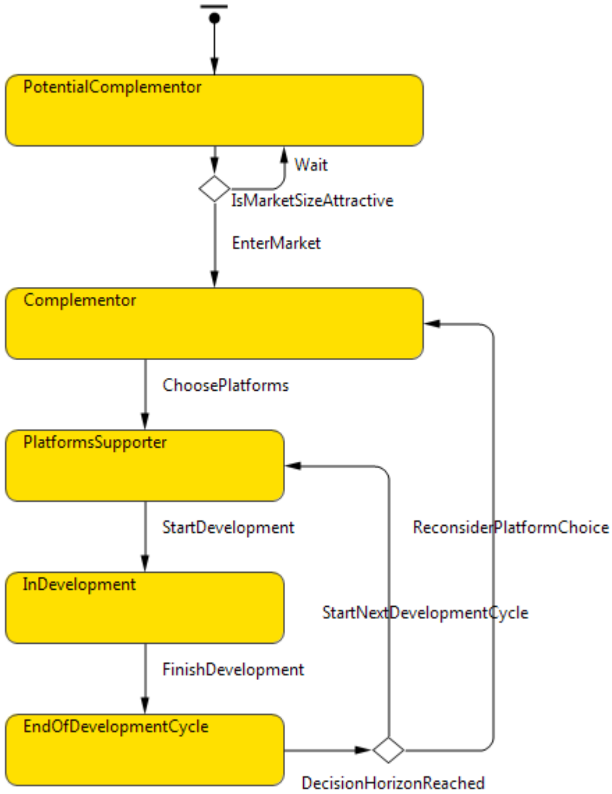
Similar to the user model, the various forms of switching costs, friction and delays are combined into a single measure, the 'decision horizon' (Lewis 2005; Ebert 1976) of a platform choice, which describes the time interval between strategic realignments. Low switching costs, of any form, are associated with a short decision horizon, and high switching costs are associated with a long decision horizon. Complementors make a platform choice based on their current market assessment. They are bound to this decision for a given decision-horizon period and develop complementary products for the chosen platform(s) during this time. Afterwards, they may revise their platform strategy if necessary.

5.1.2.3.5 Summary: Class diagram and state chart

Figure 5-8 shows the class diagram and the state chart to describe the state variables, methods and life cycle of a complementor agent. More details are provided in section 5.3.3.3.

Figure 5-8 **Complementor class diagram and state chart**

Complementor
State variables - ID : String (const) - Resource intensiveness : double (const) - Synergy level : double (const) - Decision horizon : double (const) - Supported platforms : Platform[]
Methods: - enterMarket () - choosePlatforms () - startDevelopment () - finishDevelopment () - reconsiderPlatformChoice ()



5.1.3 Process overview and scheduling

In general, computer simulations run either for a fixed period of time or until some equilibrium condition is reached (Garcia 2005). For the present model, the former approach was chosen. The model comprises a time horizon of T discrete model time steps ('ticks'), with each time step $t \in \{0, \dots, T\}$. One model time step is equivalent to a week in physical time. This relation was chosen on the basis of two considerations. First, it was intended to cover a time horizon long enough to allow the innovation diffusion process to complete, which can take up to 20 years. Second, the relation was constrained by computational requirements; a finer relation, for instance one time step equaling a day in real-time, would multiply the required computational runtime of the simulation without adding to the understanding of competition in two-sided markets. This same ratio of model time to physical time is also used by Raghu et al. (2003).

Users and complementors behave according to their decision rules. In the case that several agents act at the same time step t, their actions are executed in random order. State variables are updated immediately, whereas a controller object performs general functions such as updating market statistics and writing output data after every step.

5.2 Design concepts

The aim of this section is to place the described model in a broader perspective by addressing how common design elements of agent-based simulation research have been included in the model.

Emergence: Emergence is a key property of the model. The market-level outcome emerges from the interdependent actions of users and complementors in the two-sided market setting.

Adaptation: Both users and complementors adapt to the market environment. Changes in the competitive situation, for instance as the result of a new entrant, induces both groups of agents to reconsider their platform choice.

Objectives: Users aim to maximize utility under the constraints of imperfect information and limited cognitive abilities. Complementors aim to maximize reach, which is an adapted version of the standard profit maximization assumption.

Sensing: Constrained by both limitations of knowledge and limitation of computational capacity, users perceive the available platforms on the market, their quality and the number of complementary goods. Furthermore, they observe the platform choices of their neighbors. Complementors have perfect information about the competing platforms and their market shares.

Interaction: Interaction is directly modeled between user agents, who influence potential adopters by word of mouth. Furthermore, users communicate about their platform choice in the social network.

Stochasticity: Users are influenced by the semi-random composition of their consideration set and a stochastic quality perception bias when evaluating the platforms. Furthermore, the preferential attachment mechanism behind the scale-free network is subject to random influence.

Collectives: Users belong to a scale-free social network that affects innovation adoption and platform choice.

Observation: In order to analyze the model behavior, longitudinal data on the competitive dynamics is collected. In particular, the final state of the market is of interest. The design of experiments (section 8.2.3) discusses the dependent variable and its operationalization in greater detail.

5.3 Details

The following sections present details on the agents' properties and behavior according to the ODD model description standard. The ODD protocol prescribes three steps: first, the initialization of the model at time $t = 0$ is described; second, reference to external input data is provided; third, the submodels are explained in full detail, including the model parameters, equations and algorithms. Readers who may wish to skip this technical part are advised to refer to section 5.3.3.4, which provides an overview of the model parameters including a (very) brief description.

5.3.1 Initialization

As a first step in the initialization process, the competing platforms are added to the simulation environment. Each platform's time of entry and its quality are calculated based on the model parameters as expressed in section 5.3.3.1. Second, the user agents are added to the simulation environment, forming a scale-free social network of user agents. Both the network algorithm and the initialization of the state variables are described in section 5.3.3.2. Lastly, the complementor agents are instantiated based on the model parameters (see section 5.3.3.3). After the initialization is complete, the simulation is started by the simulation engine.

5.3.2 Input data

The calibration of the model parameters, based on empirical evidence from the smartphone industry, will be thoroughly described in chapter 7. Apart from the empirically calibrated model parameters, the model does not use external input data (in the sense of Grimm et al. 2010, p. 2765) to represent environmental processes that change over time, e.g., data imported from external files or models. Hence, this element of the ODD protocol is included only for the sake of completeness.

5.3.3 Submodels

In the following, I elaborate on the model equations, rules and algorithms. The aim is to provide a formal description of the submodels in order to allow other researchers to replicate the model results. For details on the actual implementation, please refer to the source code documentation in Appendix A. The objectives during model building were twofold: first, I strove to keep the number of parameters small while incorporating all crucial elements of platform competition in two-sided markets; second, the aim was to have standardized parameter value ranges, preferably between 0 and 1, to facilitate comparison of the effects.

5.3.3.1 Platforms

The model describes an industry with a number of technology platforms where each platform $p \in \{1, \dots, P\}, P \geq 2$ competes for control of the market.[92] The platforms vary in quality, expressed by a numerical quality index q_p. The model parameter P^{avgqual} denotes the average platform quality and can take any positive real value. The model parameter P^{qualdiff} denotes the quality difference between the best and the worst platform, relative to the average platform quality. Accordingly, $0 \leq P^{\text{qualdiff}} \leq 2$. Each platform's quality q_p is calculated based on the (exogenous) average platform quality P^{avgqual}, the (exogenous) variation in quality P^{qualdiff} and the (exogenous) number of platforms P, assuming equal quality differences q^{diff}between each of the platforms. The qualities of the best and worst platforms are denoted by q^{best} and q^{worst}:

$$q^{\text{diff}} = \frac{\left(q^{\text{best}} - q^{\text{worst}}\right)}{P-1} = \frac{\left(P^{\text{avgqual}} \times P^{\text{qualdiff}}\right)}{P-1},$$

$$q^{\text{worst}} = P^{\text{avgqual}} - \frac{\left(P^{\text{avgqual}} \times P^{\text{qualdiff}}\right)}{2},$$

$$q_p = q^{\text{worst}} + (p - P) \times q^{\text{diff}}.$$

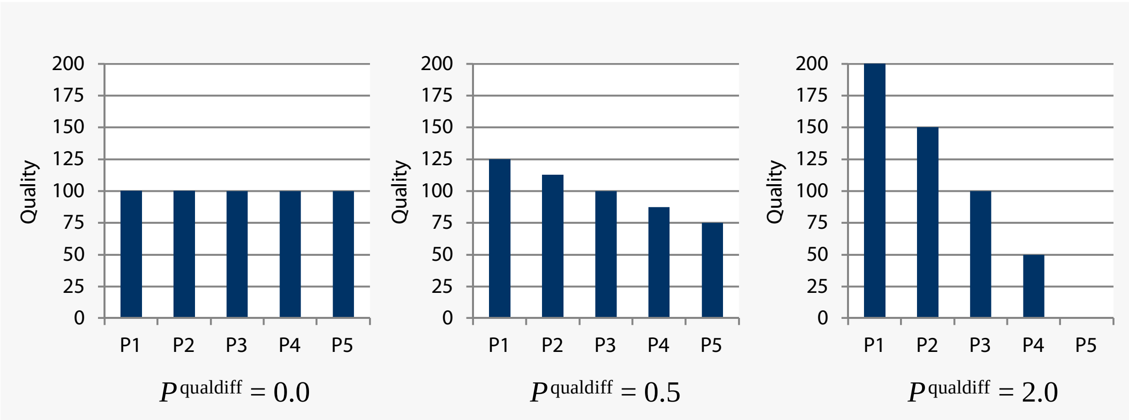
As a result, the platforms are sorted by descending quality: platform 1 is superior to platform 2, which is superior to platform 3, etc. Hence, $q_p > q_{p+1}$ holds for every p if $P^{\text{qualdiff}} > 0$, and

92 Although the conceptual model portrays an industry with an arbitrary number of firms, the computational model is restricted to a maximum of five platforms for visualization reasons. For simplicity, the platforms will later be referred to with capital Latin letters, so that platform 1 is termed platform A, platform 2 is termed platform B, and so forth.

platform 1 is always the best platform. Obviously, if $P^{\text{qualdiff}} = 0$, all platforms are of equal quality $q_p = P^{\text{avgqual}}$.

To summarize, Figure 5-9 shows the impact of the quality difference model parameter.

Figure 5-9 **Platform quality differences**
Left: no quality difference, $P^{\text{qualdiff}} = 0.0$
Middle: medium quality difference, $P^{\text{qualdiff}} = 0.5$
Right: maximum quality difference, $P^{\text{qualdiff}} = 2.0$
(for $P^{\text{avgqual}} = 100$; $P = 5$)



Let m_p be the time of market entry for platform p. The model parameter P^{timediff} denotes the interval between the first and the last market entry, relative to the total model time T. Therefore, $0 \le P^{\text{timediff}} \le 1$. The platforms enter the market either simultaneously $\left(P^{\text{timediff}} = 0\right)$ or successively $\left(P^{\text{timediff}} > 0\right)$, so that $0 \le m_p \le T$. In case of successive market entry, it is assumed that the quality of the entering platforms improves over time, i.e., new entrants are of better quality than incumbent platforms. Given that the platforms are sorted by descending quality, $m_p \ge m_{p+1}$. The worst platform P enters first at time $t = 0$, and the best platform (platform 1) enters last.

Each platform's market entry time m_p is calculated based on the (exogenous) entry timing difference parameter P^{timediff}, the (exogenous) total model time T and the (exogenous) number of platforms P, assuming equal intervals m^{diff} between the market entries. The entry time of the last platform is denoted by m^{last}:

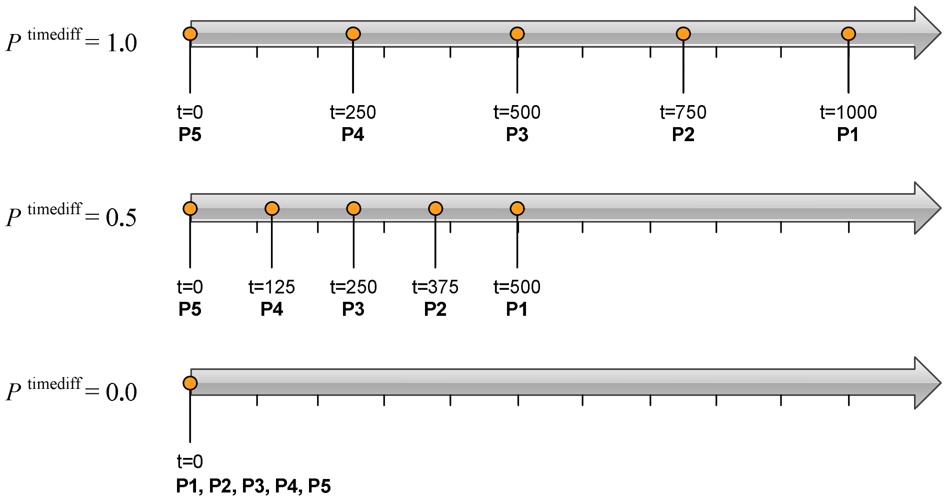
$$m^{\text{last}} = P^{\text{timediff}} \times T,$$

$$m^{\text{diff}} = \frac{m^{\text{last}}}{P-1},$$

$$m_p = m^{\text{last}} - (P - p) \times m^{\text{diff}}.$$

To summarize, Figure 5-10 shows the impact of the entry timing model parameter.

Figure 5-10 **Platform market entry timing**
Top: slow successive entry, $P^{\text{timediff}} = 1.0$
Middle: rapid successive entry, $P^{\text{timediff}} = 0.5$
Bottom: simultaneous market entry, $P^{\text{timediff}} = 0.0$
(for $T = 1000$; $P = 5$)



The number of complementary products for platform p at time t is denoted by $g_{p,t}$.

5.3.3.2 Users

Each user agent $u \in \{1, \ldots, U\}$ adopts the innovation according to the Bass diffusion model. User agents are in one of two possible states:

S^{PA} = 'potential adopter', with the total number of potential adopters at time t denoted by S_t^{PA},

S^{A} = 'adopter', with the total number of adopters at time t denoted by S_t^{A},

so that $S_t^{\text{PA}} + S_t^{\text{A}} = U$ holds for each point in time.

The user agents are embedded in a scale-free social network where the scale-free parameter M (Barabási & Albert 1999) equals the model parameter D^{m}. The number of links of a user agent is denoted by k_u. Following Rahmandad & Sterman (2008, see the e-companion of the paper), the network algorithm starts with D^{m} initial user agents connected to each other in a ring and then adds the rest of the $U - D^{\text{m}}$ agents to the network one at a time. Each new user agent is connected to previous agents through D^{m} new links, where the probability that the new agent will be connected to another agent u is $\frac{D^{\text{m}} \times k_u}{\sum_u k_u}$.

The modeling of the Bass diffusion process is based on an agent-based implementation of a system dynamics model by Sterman (2004).[93] For each user agent, innovation adoption due to external influence is triggered by means of a timeout drawn from an exponential distribution $\lambda e^{-\lambda x}$ with $\lambda = D^{\text{ext}}$, given that the agent is still in state S^{PA}. Immediately after adoption, adopters engage in word-of-mouth communication to influence other potential adopters. In the model, adopters send a message to a randomly connected agent that triggers adoption if the receiver agent has not yet adopted. Messages are sent repeatedly with a recurrence time drawn from an exponential distribution with $\lambda = D^{\text{wom}}$. In order to reduce undesired variance in the diffusion process, the samples of the exponential distributions are drawn using a custom random number generator with constant seed value. Accordingly, the diffusion patterns of repeated runs with constant values for D^{ext} and D^{wom} are roughly identical, except for a marginal effect from the randomness of the scale-free network topology.

For the information search, the agents' limitation of knowledge is described by the model parameter $U^{\text{infolevel}}$, with $0 \leq U^{\text{infolevel}} \leq 1$. The limitation of knowledge constrains the size of the consideration set V_u so that $|V_u| = U^{\text{infolevel}} \times P$, rounded to the nearest integer but with a minimum size of 1. In the case of perfect information ($U^{\text{infolevel}} = 1$ and thus $|V_u| = P$), users evaluate all platforms in the marketplace. If information is extremely limited ($U^{\text{infolevel}} = 0$), the minimum size of the consideration set is set to 1. Users fill their consideration set by first asking for recommendations from other adopters in their social network. In order to represent this in the model, users send a message to all directly connected agents, who respond by recommending the platform they have already chosen, if any. After removing duplicate answers, the recommended platforms become part of the consideration set. Accordingly, users have knowledge of the platforms of connected agents. The remaining slots of the consideration set, if any, are filled by other, randomly selected platforms, which represents an information search using other external sources.

For decision-making, agents evaluate the platforms included in their consideration set. Let $Util_{p,t}$ denote the utility of choosing platform p at time t, comprising of the inherent value $Util^{\text{inh}}$ and the network value $Util^{\text{nwk}}$ derived from the availability of complementary goods:

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93 The implementation is similar to the diffusion model included in the *AnyLogic* 6.5.1 tutorial by *XJ Technologies*.

$$Util_{p,t}\left(q_p, g_{p,t}\right) = Util^{\text{inh}}\left(q_p\right) + Util^{\text{nwk}}\left(g_{p,t}\right).$$

Agents are boundedly rational and cannot perfectly assess the quality of a platform. The agents' limitation of computational capacity is described by the model parameter $U^{\text{ratiolevel}}$, with $0 \leq U^{\text{ratiolevel}} \leq 1$. The inherent value of a platform is given by the inherent quality of the platform q_p biased by a stochastic error term ρ:

$$Util^{\text{inh}}\left(q_p\right) = q_p + \rho\,,$$
$$\rho \sim \mathcal{N}\left(0, \sigma^2\right),$$

where ρ is drawn from a normal distribution with a mean of zero and variance σ^2. The standard deviation σ is a function of the quality perception bias $1 - U^{\text{ratiolevel}}$, calibrated by the average platform quality parameter P^{avgqual}:

$$\sigma = \frac{1}{2}\left(1 - U^{\text{ratiolevel}}\right) \times P^{\text{avgqual}}\,.$$

When $U^{\text{ratiolevel}} = 1$, users can perfectly assess the quality of a platform. In case $U^{\text{ratiolevel}} = 0$, their perception significantly deviates from the objective value.

The network value of a platform depends on the number of complementary products $g_{p,t}$ that are available for the platform at that time. The network utility curve is represented by a concave bounded utility function (Lilien & Rangaswamy 2004), mathematically expressed by a modified exponential function:

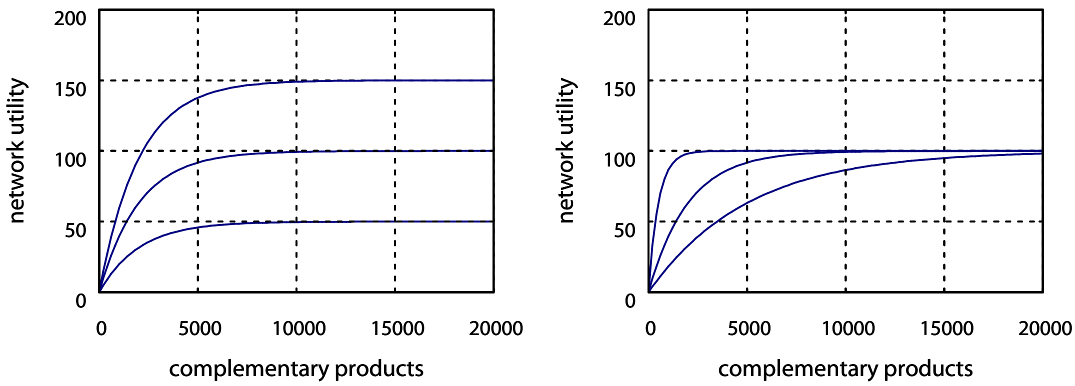
$$Util^{\text{nwk}}\left(g_{p,t}\right) = \alpha\left(1 - e^{-\frac{\beta}{1000} g_{p,t}}\right) + \gamma, \qquad \alpha, \beta, \gamma \geq 0$$

where

α	=	$f\left(U^{\text{nwkeffect}}, P^{\text{avgqual}}\right)$, the upper limit of network utility,
β	=	U^{utilgrad}, which describes the gradient and saturation point of the utility curve,
γ	=	0, so that the network-derived utility is zero when there are no complementary products available for a platform.

Figure 5-11 depicts the utility curve for different parameter values.

Figure 5-11 **Concave bounded utility curve: upper limit and gradient**
Left figure: impact of limit parameter, $\alpha \in \{50;\ 100;\ 150\}$, $\beta = .0005$, $\gamma = 0$
Right figure: impact of gradient parameter, $\alpha = 100$, $\beta \in \{0.0002;\ 0.0005;\ 0.002\}$, $\gamma = 0$



The network effect factor (Buxmann 2001) describes the importance of the indirect network effect in relation to the total value of a platform, comprising of inherent value and the network value.

Drawing on this concept, the model parameter $U^{\text{nwkeffect}}$ describes the relative strength of the indirect network effect in the modeled market ($0 \leq U^{\text{nwkeffect}} \leq 1$), based on the maximum network value α and the platforms' average inherent value P^{avgqual}:

$$U^{\text{nwkeffect}} = \frac{\alpha}{\alpha + P^{\text{avgqual}}}.$$

When $U^{\text{nwkeffect}} = 0$, users do not value complementary products at all and there is no indirect network effect. The higher the value of $U^{\text{nwkeffect}}$, the more important complementary products are. As $U^{\text{nwkeffect}}$ approaches 1, the indirect network effect is the single source of utility. In other words, the platform is of no use in the absence of complementary products. For instance, this is the case for a *Blu-ray* player without any available *Blu-ray* discs.

Based on the previous equation, the upper limit α of the network utility function can be rewritten as a function of the two model parameters:[94]

$$\alpha = \frac{U^{\text{nwkeffect}} \times P^{\text{avgqual}}}{1 - U^{\text{nwkeffect}}}.$$

[94] Please note that for positive values of P^{avgqual} and $U^{\text{nwkeffect}} = 1$, α is undefined.

Ultimately, users choose the platform p from their consideration set V_u that has the highest aggregate utility as expressed by:

$$\max\left(Util_{p,t}\left(q_p, g_{p,t}\right)\right) = \max\left(Util^{\text{inh}}(q_p) + Util^{\text{nwk}}(g_{p,t})\right).$$

In conclusion, users are boundedly rational and aim to maximize utility, but under the constraints of imperfect information and limited cognitive abilities.

The number of users of platform p at time t is denoted by $u_{p,t}$. Accordingly, platform p's market share in terms of the installed base at time t is given by

$$ib_{p,t} = \frac{u_{p,t}}{S_t^{\text{A}}}$$

if at least one user has adopted the innovation, so in case that $S_t^{\text{A}} > 0$.

By definition, the sum of the market shares equals 100 percent:

$$\sum_{p=1}^{P} ib_{p,t} = 1.$$

As a proxy for switching costs, users are bound to their platform choice for a decision-horizon period h_u, measured in model time steps, after which they may switch to another platform. The decision-horizon parameter U^{horizon}, $0 \leq U^{\text{horizon}} \leq 1$, is defined relative to the total model time T, so that $h_u = U^{\text{horizon}} \times T$.

5.3.3.3 Complementors

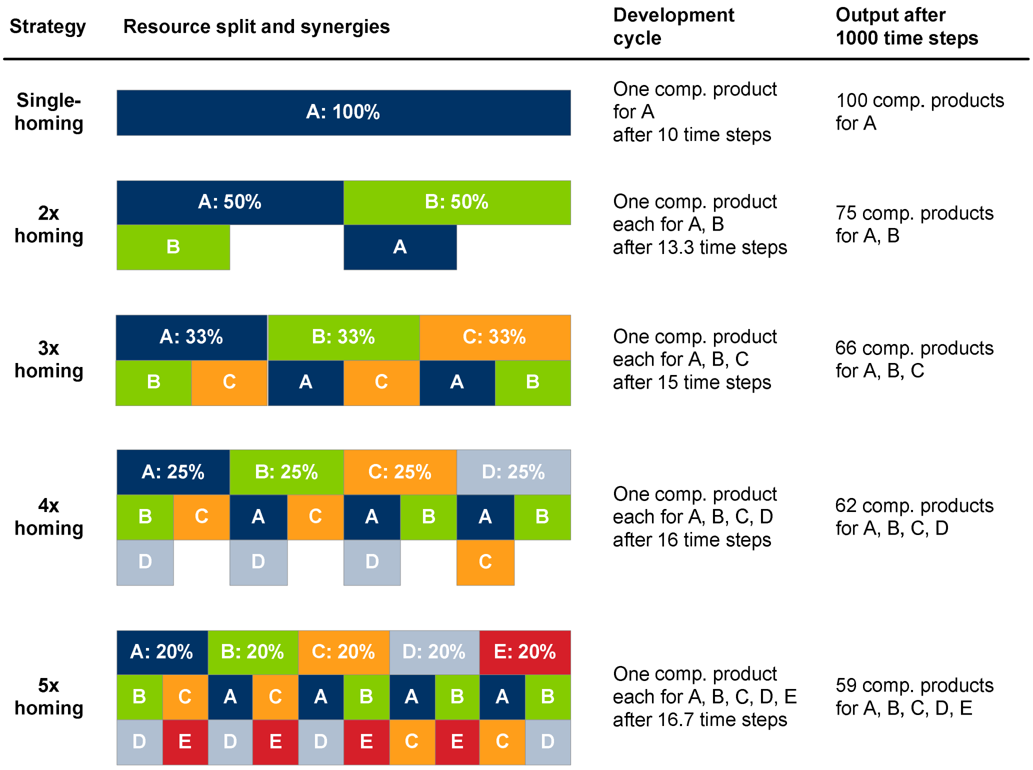
Each complementor agent $c \in \{1, \dots, C\}$ joins the market to provide complementary products for either one or multiple platforms as soon as the agent perceives the overall market size to be sufficiently attractive. For this reason, complementors continually observe the market size at each time step t. Since complementors anticipate the future growth of the market, they enter the emerging industry earlier than users on average. Hence, complementors can be regarded as early adopters whose 'speed of adoption' is ten times higher than that of users. For instance, when 2 percent of the users have adopted the innovation, 20 percent of complementors have already entered the market.

Complementors devote their resources, measured in model time steps, to developing complementary products for either one or multiple platforms. The model parameter C^{res} denotes the resource intensiveness of development, i.e., the number of model time steps that are needed to develop one complementary product for a *single* platform. However, complementors may benefit from synergies when the same complementary product is developed for multiple platforms. The model parameter C^{synlevel} describes the synergy level for multi-platform development and depends on the level of compatibility between the platforms. For instance when $C^{\text{synlevel}} = 0.5$, 50 percent of the complementors' resources can be used for multi-platform development. Let the platform strategy of a complementor, i.e., the number of platforms to support, be given by $s_c \in \{1, \dots, P\}$ so that $s = 1$ describes single-homing, with only the largest platform supported, and $s_c = P$ describes the extreme multi-homing case, with all platforms available on the market supported. Furthermore, d_c denotes the development cycle of a complementor agent, defined as the number of time steps that are needed to finish the development of one complementary product in the case of either single- or multi-homing. In the case of single-homing, $d_c = C^{\text{res}}$. In the case of multi-homing, d_c depends on the resource intensiveness C^{res} , the number of supported platforms s_c and the synergy level C^{synlevel}:

$$d_c\left(C^{\text{res}}, s_c, C^{\text{synlevel}}\right) = \frac{C^{\text{res}}}{\frac{1}{s_c}\left(1 + C^{\text{synlevel}} \times (s_c - 1)\right)}.$$

Accordingly, the more platforms that are supported, the longer the development cycle. The development cycle also increases with lower synergy levels and higher resource intensiveness of development. The following figure depicts the synergy effect under various platform strategies. It demonstrates the impact on the length of the development cycle d_c and the number of complementary products per time period, i.e., the 'output' of a complementor agent.

Figure 5-12 **Synergy effects from different platform strategies**
Example for one complementor agent, $C^{res} = 10; C^{synlevel} = 0.5$



In the case of single-homing, a complementor agent fully devotes resources to developing for a single platform A. The agent completes the development cycle d_c after 10 time steps, equal to C^{res}. After 1,000 time steps, the result is a total output of 100 complementary products for platform A. In the case of 2x-homing, the agent decides to support two platforms, A and B. The complementor splits the resources 50:50 between the two platforms. In this case, 50 percent ($C^{synlevel} = 0.5$) of the development resources are also beneficial for multi-platform development, creating 'virtual resources' from synergies between the two platforms. The complementor agent finishes the development cycle after 13.3 time steps. This results in a total output of 75 complementary products for platform A and B after 1,000 time steps. The logic is the same for the remaining strategies. In the extreme case of 5x-homing, all five platforms are supported. The development cycle takes 16.7 time steps. After 1,000 time steps, the complementor has developed a total of 59 complementary products for all five platforms.

In order to decide on their platform strategy, complementors balance the longer development cycle when supporting multiple platforms with the benefits of greater market coverage. For instance, they determine whether it is more beneficial to provide 100 complementary products for platform A ('single-homing') compared to providing 75 complementary products for A and B ('2x-homing') in the same time period. In this regard, complementors maximize the expected *reach*. Given that the platforms are ordered by descending market shares, the expected reach of a strategy s_c at time t is denoted by

$$\hat{r}_{s,t} = \left(\sum_{p=1}^{s} \widehat{ib}_{p,t+d_c} \right) \times \frac{C^{\text{horizon}}}{d_c}.$$

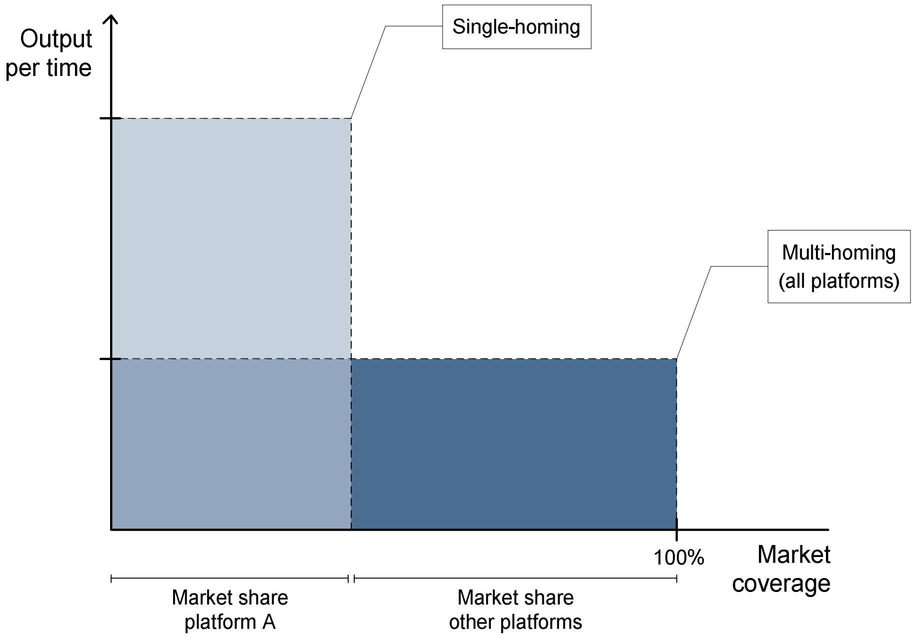
The formula shows that the expected reach $\hat{r}$ equals the potential user base multiplied by the output (i.e., the number of complementary products) in a given period of time. Thus, the expected reach serves as a proxy for sales potential. Under the assumption that sales opportunities, pricing and development cost (which lie beyond the scope of this model) are independent of the platform, the optimal strategy is to maximize reach.

The reach-maximizing strategy is determined by the expected market shares at the end of the development cycle $\widehat{ib}_{p,t+d_c}$ and the synergy level C^{synlevel}. It is assumed that complementors are not forward-looking and thus do not form expectations about the future competitive situation, so that $\widehat{ib}_{p,t+d_c} = ib_{p,t}$. Complementors choose the platform strategy that maximizes their expected reach:

$$\max\left(\hat{r}_{s,t}\left(ib_{p,t}, C^{\text{synlevel}} \right) \right).$$

Figure 5-13 visualizes the optimization task by comparing two extreme cases.

Figure 5-13 **Reach-maximizing strategy for complementors**
Example: single-homing for platform A vs. multi-homing for all platforms *P*.
Reach is equal to the area of the rectangle. Note that the difference in output levels depends on the synergy level for multi-platform development.



The table below shows the reach-maximizing strategy under different market-share scenarios for $C^{res} = 10$ and $C^{synlevel} = 0.5$.

Table 5-2 **Optimal platform strategy under different market share scenarios**
$P = 5;\ C^{res} = 10; C^{synlevel} = 0.5$

	Market share scenarios					*Reach*				
	Platform					*Single-homing*	*2x homing*	*3x homing*	*4x homing*	*5x homing*
	A	*B*	*C*	*D*	*E*					
(1)	80%	5%	5%	5%	5%	**4.17**	3.32	3.13	3.10	3.13
(2)	60%	25%	5%	5%	5%	3.13	**3.32**	3.13	3.10	3.13
(3)	50%	25%	20%	2.5%	2.5%	2.61	2.93	**3.30**	3.18	3.13
(4)	40%	30%	20%	7.5%	2.5%	2.09	2.74	3.13	**3.18**	3.13
(5)	20%	20%	20%	20%	20%	1.04	1.56	2.09	2.61	**3.13**

Note: Reach maximizing strategies are given in bold.

Scenario (1) shows that in a very concentrated market with one dominant platform, single-homing is the best strategy for complementor agents. The additional development effort to support a second platform is substantial, given synergies of $C^{synlevel} = 0.5$. Moreover, supporting a second platform would increase market coverage by only 5 percent. In this scenario, it is efficient to concentrate on the largest platform and to increase the number of complementary products per time period instead of choosing a multi-homing strategy.[95] Scenarios (2)–(4) describe a situation with some major and some minor platforms. Here, complementors have to carefully evaluate the trade-off between higher market coverage and longer development cycles. The best strategy varies from 2x-homing to 4x-homing depending on the particular market-share scenario. Scenario (5) is composed of five platforms with equal market shares. In this case, complementors can fully leverage development synergies by supporting all five platforms, which is the dominant strategy in this setting.[96]

Complementor agents can adjust their platform strategy if necessary. As a proxy for switching costs, complementors are bound to their platform strategy for a given decision-horizon period h_c, measured in model time steps. The decision-horizon parameter C^{horizon}, $0 \leq C^{\text{horizon}} \leq 1$, is defined relative to the total model time T, so that $h_c = C^{\text{horizon}} \times T$.

5.3.3.4 Summary of model parameters

To conclude the model description chapter, the table below provides an overview of all 19 model parameters including their symbol, their data type and value range, as well as a brief description.

95 In the case of no synergies between the platforms ($C^{\text{synlevel}} = 0$), single-homing for the largest platform is always the dominant strategy, independent of the market shares of the other platforms.

96 Please note that the chosen method of modeling the multi-homing decision for complementors works well for a relatively small number of platforms, i.e., up to five. With more platforms, multi-homing for all platforms quickly becomes the optimal strategy under most market-share scenarios due to the unbounded synergy mechanism. This undesired effect could be resolved by including a second parameter that limits the maximum number of platforms that can be supported. For instance, this second parameter could account for the additional overhead of supporting an additional platform. For the present model, the described decision logic is fully sufficient and helps to keep the number of model parameters small.

Table 5-3 **Summary of model parameters**

Input variable	*Symbol*	*Domain*	*Type*	*Value range*	*Short description*
Number of time steps	T	Environment	int	100..3,000	Model time, the number of discrete model time steps ('ticks')
Number of runs	R	Environment	int	1..5,000	Repetitions per parameter setting
Number of platforms	P	Environment	int	2..5	Number of competing technology platforms
Number of users	U	Environment	int	30..2,500	Number of user agents
Number of complementors	C	Environment	int	0..100	Number of complementor agents
Network: scale-free M	D^{m}	Diffusion	int	1..10	Barabási-Albert (BA) model parameter: minimum number of links of an user agent
Bass model: external effect	D^{ext}	Diffusion	double	0..1 x 10^{-5}	Bass model parameter: intensity of external influences, such as advertising
Bass model: word-of-mouth	D^{wom}	Diffusion	double	0..0.1	Bass model parameter: intensity of word-of-mouth communication
Information level	$U^{\mathrm{infolevel}}$	Users	double	0..1	Agents' limitation of knowledge: constrains the size of the consideration set
Rationality level	$U^{\mathrm{ratiolevel}}$	Users	double	0..1	Agents' limitation of computational capacity: determines the perception bias
Network effect factor	$U^{\mathrm{nwkeffect}}$	Users	double	0..0.999	Relative strength of network effect: value from complementary products in relation to the total value of a platform
Utility function: gradient	U^{utilgrad}	Users	double	0..1	Gradient of the utility curve: describes how quickly indirect network effects 'kick in'
Decision horizon	U^{horizon}	Users	double	0..1	Ease of switching: a proxy for switching costs
Resource intensiveness	C^{res}	Complementors	double	0..50	Resource intensiveness of development: number of model time steps needed to provide one complementary product for a single platform
Synergy level	C^{synlevel}	Complementors	double	0..1	Synergy level for multi-platform development: how much effort is it to provide complementary products for multiple platforms
Decision horizon	C^{horizon}	Complementors	double	0..1	Ease of switching: how often do complementors reconsider their platform strategy
Average quality	P^{avgqual}	Platforms	double	0..1,000	Average platform quality, expressed by an objective quality index
Variation in quality	P^{qualdiff}	Platforms	double	0..2	Quality difference between the best and the worst platform, relative to the average platform
Entry timing difference	P^{timediff}	Platforms	double	0..1	Interval between the first and the last market entry, relative to the total model time (corresponds to the speed of technological progress)

6 Empirical case: platform competition in the smartphone industry

Having described the generic simulation model for path dependence in two-sided markets, I now elaborate on the empirical case to which the model will be applied: platform competition in the global smartphone industry. Much of the research on path dependence has been devoted to retrospective cases. By focusing on the emerging smartphone industry, this study adds a new dimension to path dependence research by bringing in a forward-looking, *prospective* perspective. The importance of empirical calibration for simulation research as well as the benefits of the chosen application will be thoroughly discussed in chapter 7, for which this chapter on the empirical case serves as preparation.[97]

First, a brief introduction is given to highlight the significance of the evolving smartphone industry. Second, the terms *smartphone platform* and *ecosystem* are defined to provide the reader with a sound understanding of the interrelated actors in this two-sided market. Third, I describe today's competitive situation and provide an outlook on some of the future developments that will be affected by the outcome of the ongoing platform competition. Undoubtedly, it is not simply a technical issue between various operating systems, but rather a technological force that shapes the world in which we live in.

6.1 An introduction to the smartphone industry

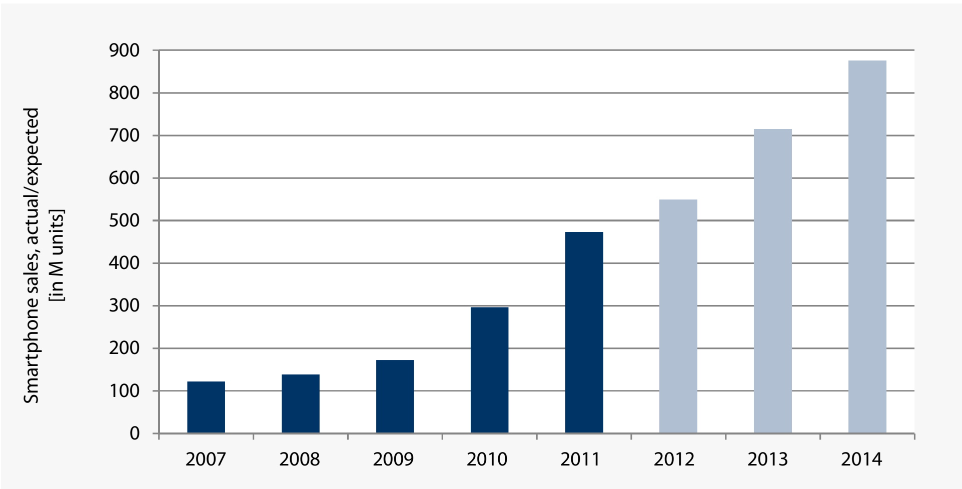
The internet has transformed modern day life. The reasons are two-fold. First, the internet has changed the way we access and process information. It provides us with virtually unlimited information, instantly available at our fingertips, both in our professional and personal lives. Second, the internet has changed the way we communicate with others, which is the essence of human society. Communication takes place around the globe, instantly and at no cost, either in anonymity or in social network communities of similar interests and values. We work collaboratively online by sharing ideas, knowledge and skills. The internet has become a "natural, background part of everyday life" (Bargh & McKenna 2004).

[97] This chapter was written in cooperation with Frithjof Stöppler. Fruitful discussions and valuable comments on the draft are gratefully acknowledged.

Smartphones take this development to a new level by offering high-speed, 'always-on' mobile internet access in addition to the traditional features of classic mobile phones. As early as 2003, Manasian (2003) anticipated that "we are heading towards a networked society of ubiquitous, mobile communications". With the widespread adoption of smartphones around the world, this situation has arrived. People now carry the world's information in their pocket, and mobile internet on smartphones is changing the way we access, create and share information. Unlike other technological devices such as laptops, there is a "unique relationship between people and their phones. It's the one piece of technology they have with them all the time, keeping them connected to information, family, friends and coworkers" (Lees 2010). In this regard, the smartphone is at the "epicenter of the digital and physical worlds" (Grech 2011) — in the sense that people use it to connect to the digital world wherever they physically are.

Consumers have quickly adopted this new technology, a trend which can be clearly seen by looking at the global sales statistics and projections for smartphones illustrated in Figure 6-1.

Figure 6-1 **Worldwide smartphone sales 2007-2011 and sales projections 2012-2014**
(Data source: Gartner 2009, 2010d, 2011b, 2012a)



Smartphone sales have grown rapidly over the past years. Between 2007 and 2011, global unit sales increased substantially, from 122 million units in 2007 to 472 million units in 2011 (Gartner 2009, 2012).[98] Within this time frame, the smartphone industry experienced its

[98] This means that smartphones have surpassed personal computers based on shipments numbers in 2011 (Canalys 2012).

strongest growth in the year 2010, with an increase of 72 percent compared to 2009 (Gartner 2011b).

Most industry experts forecast continued double-digit growth for the smartphone industry for the coming years (IDC 2011c; Gartner 2010d). Global sales numbers remaining for 'classic' mobile devices confirm this positive outlook: in 2010, worldwide mobile device sales *excluding* smartphones reached 1.3 billion units (Gartner 2011b).[99] Given that a large fraction of these devices will soon be substituted by smartphones, there is plenty of room for market growth.[100] As shown in Figure 6-1, projections by *Gartner* (2010d) estimate annual smartphone sales at 876 million units in 2014, which translates to an average year-on-year growth of 23 percent between 2011 and 2014. Other industry experts even expect annual sales to surpass 1 billion units by 2014 (Reuters 2012b).

To further demonstrate the increased public interest in smartphones, I analyze search engine queries for 'smartphones' between 2004 and 2010. Search engine data is a novel way of measuring social phenomena by delivering insights into what the world is searching for. The *Google Insights for Search* research tool provides aggregated data on the relative frequency of search terms entered by internet users across time and geographic units. This method has been found to correspond closely with existing measures of social phenomena (Scheitle 2011) and has been successfully applied in the social sciences (see for instance Preis et al. 2011; Varian & Choi 2009). Figure 6-2 compares the public interest in smartphones, measured by normalized Google search volume[101], with quarterly sales data for smartphones between 2007 and 2010.

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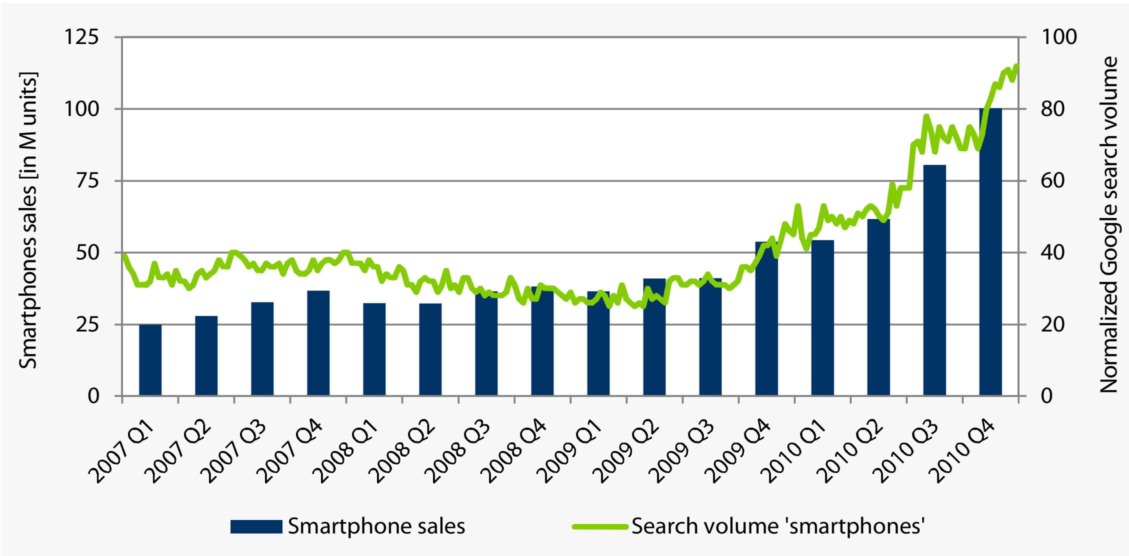
99 Moreover, 1.6 billion devices sold per annum, including 'classic' mobile phones and smartphones, emphasizes the remarkable role of mobile communications in general.

100 In the fourth quarter of 2010, smartphone sales already accounted for close to 50 percent of all handsets sold in Western Europe and North America (Gartner 2011b). This indicates the substitution trend, which can also be extrapolated for other regions. For instance, Africa is the world's fastest growing market for mobile devices, and smartphone penetration there has already reached six to eight percent (Reuters 2012a). This development is facilitated by affordable low-end smartphones which provide internet access to many users for the first time in their lives. Also, "since mobile-phone coverage is far better than fixed-line availability, the result has been that the cellphone is swiftly becoming Africa's computer of choice" (Economist 2011d).

101 *Google Insights for Search* (http://www.google.com/insights/search/) computes how many searches have been conducted for a specific search term, relative to the total number of

Figure 6-2 **Public interest in smartphones and quarterly smartphone sales data**
(Data source: Google Insights for Search database; Gartner 2008a, 2008b, 2008c, 2009, 2010b, 2010c, 2010e, 2011b; own calculations)



The empirical data shows that the year 2010 was a landmark in the evolution of the industry, as smartphones were clearly heading for the mass market. Public interest in smartphones has risen strongly since the third quarter of 2009. Furthermore, the data reveals a clear correlation between the relative number of search queries and quarterly sales. Normalized search engine volume for smartphones has tripled between the third quarter 2009 and the fourth quarter 2010. In the same period, smartphone unit sales grew by 144 percent to 100.1 million units. This correlation could be explained by consumers either searching for information in the pre-purchase phase and/or consumers looking for help in the post-purchase phase.

To summarize, smartphones have gained tremendous importance in recent years, both in economic terms but also in other measures of public interest. This trend is widely expected to continue.

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searches. The data is provided on a weekly basis. The week with the highest search volume is given a score of 100. All other cases are normalized accordingly on a scale of 0 to 100. For example, comparing a score of 25 with a score of 100, the latter term was searched for four times as often as the former term (Scheitle 2011; Google Insights for Search help section: http://www.google.com/support/insights/).

6.2 Defining a smartphone platform and its ecosystem

This section lays the foundation for a thorough understanding of the smartphone industry and ties the empirical case back to the theory of two-sided markets. The term *smartphone* is defined, and the role of smartphone platforms and ecosystems are explained in detail.

There is no common, industry-wide standard of what constitutes a smartphone (Hamblen 2009). However, all definitions share the understanding that a smartphone brings together computer functionality with a wireless voice device.[102] *Gartner*, one of the leading global IT research and consulting firms, defines a smartphone as “a large-screen, voice-centric handheld device designed to offer complete phone functions while simultaneously functioning as a personal digital assistant (PDA)” (Gartner 2004, p. 322). *IDC*, another major market research firm specializing in IT and telecommunications, defines smartphones as *converged mobile devices*: “a subset of mobile phones, converged mobile devices feature a high-level operating system that enable the device to run third-party applications in addition to voice telephony” (IDC 2009). This definition highlights the importance of a sophisticated operating system and the extendibility by way of third-party software applications.

It has been stressed that smartphones combine the features of mobile phones and computers systems. The technological and economic convergence of previously separated markets completely transformed the competitive environment.[103] This transformation was largely driven by the redefined role of the operating system. Until recently, mobile phone makers programmed proprietary operating systems (OS) for their handsets, and most consumers were unaware of the underlying software system on their device. Operating systems were “invisible engines” (Evans et al. 2006) which had no impact on consumers’ purchasing decisions. This has changed. Similar to the choice between *Mac OS* or *Windows* for a PC system, the smartphone’s operating system now plays a central role for consumers.

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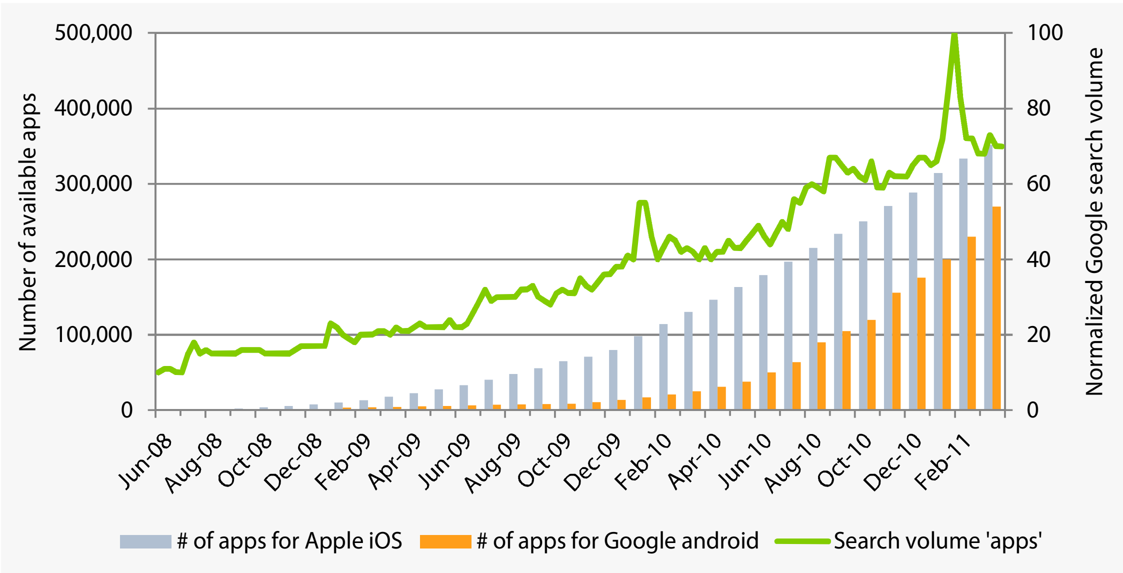
102 Even though different definitions for smartphones are used, market research firms tend to report roughly the same numbers of smartphone shipments (Hamblen 2009). This indicates that there is a shared understanding in the industry of what separates a smartphone from other, more low-end mobile phones which are predominantly used for mobile telephony and lack the characteristics of modern smartphones described above.

103 See also chapter 6.3 on convergence.

In addition to providing the phone's user interface, the operating system establishes the basis from which to extend the system's functionality with third-party software applications, commonly referred to as *apps*. Apps cover a wide range of services and subjects: mobile shopping, media consumption, social networking, productivity tools and games, to name but a few examples.[104] The possibilities are endless and the operating system serves as the technical basis for the programming of third-party mobile applications. As a result, apps are developed for one specific operating system and are incompatible with other smartphone platforms.

The use of third party software applications has become highly popular with smartphone users. Figure 6-3 reports the public interest in apps, measured by search engine usage, and the availability of apps for two major smartphone platforms on a monthly scale between June 2008 and March 2011.

Figure 6-3 **Public interest in apps and number of apps available for two major platforms**
(Data source: Google Insights for Search database; 148apps.biz 2011; AndroLib.com 2011; own calculations)



104 For instance, with apps consumers can connect with friends on *Facebook*, the world's largest social networking site with more than 845 million active users worldwide in 2011 (Facebook 2012). Apps help to find the nearest public transport station or the shortest route in a foreign city. Apps guarantee shoppers get the best deal by comparing prices using the smartphone's camera as a barcode scanner. Apps offer entertainment on the road with a myriad of different games available for all platforms. Apart from the consumer market, a variety of business apps let executives manage customer relationships with their mobile devices, allow them to check order logs and inventories on the go, or help them manage their travel plans.

As revealed by the data above, public interest in apps has risen steadily between 2008 and 2011.[105] Parallel to the increased public interest in apps, the number of apps available for smartphone platforms also increased strongly. Figure 6-3 shows data on the two most prominent platforms, *Apple's iOS* and *Google Android*. *Apple* was the first company to establish a successful portfolio of third-party apps for their *iPhone* device family. As of March 2012, about 550,000 apps were available to *iPhone* users in 123 countries (Apple 2012). Entering the mobile apps business six months later, *Google* has also managed to gather a large number of application developers for its *Android* platform. By the beginning of 2012, *Android* users could choose from about 400,000 apps for their smartphones (Myslewski 2012).

In addition to the sheer number of apps available, consumers also make heavy use of these new opportunities. For instance, *Apple* announced that it had reached one billion downloads just nine months after opening its application store for the *iPhone* (Apple 2009a). By March 2012, *Apple's App Store* had already reached 25 billion downloads (Apple 2012). On average, *iPhone* users have installed 28 apps on their device vs. an average of 17 apps for *Android* users (Mobclix 2010). Revenues from mobile apps, consisting of purchased applications and in-app advertising, are projected at 15.1 billion U.S. dollars in 2011, with a long-term growth forecast of over 1,000 percent between 2010 and 2014 (Gartner 2011a). Undoubtedly, apps are a crucial element of customers' value proposition when buying a smartphone (Goldman Sachs 2009).

What are the consequences of this "app revolution" (Sobhany 2011)? For device makers, a go-it-alone strategy with proprietary software operating systems for their devices is becoming increasingly impractical, because software developers require standardized operating systems for the development of mobile apps. Furthermore, as smartphones become more sophisticated in terms of hardware complexity and feature scope, the demand for more powerful operating systems increases, and handset makers are incentivized to share development costs. Both the need for compatibility and rising costs have promoted the process of standardization and enforced a consolidation of smartphone operating systems.

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105 The timeline shows two notable peaks in search engine usage on 'apps', one in January 2010 and one in January 2011. An explanation could be that new smartphone users want to explore the potential of their new devices, as smartphone sales were particularly strong in the fourth quarter of 2009 and 2010 due to the holiday season (see Figure 6-1).

It is important to think of a smartphone operating system as the core of a smartphone *platform* that provides the basis for a whole business ecosystem (Evans et al. 2006; Lin & Ye 2009). Particularly for software platforms, the term "business ecosystem" (Moore 1993) is frequently used to describe the symbiotic relationships between the platform provider, independent firms and consumers, which together form a mutually dependent community (Evans et al. 2006). Drawing an analogy between business networks and biological ecosystems, business ecosystems borrow the notion of a "food web" to describe the flow of value and revenues in a platform market (Iansiti & Levien 2004; Lin & Ye 2009).

At least four different actors participate in a smartphone ecosystem:

1. The *platform provider* supplies and controls the *smartphone platform*, consisting of a smartphone operating system and an official application store. (a) The *operating system* serves as an intermediary between software applications and the phone's hardware (Evans et al. 2006). In this role, it creates the basis for the ability to extend the system's functionality with third-party software apps by making services available through application programming interfaces (APIs). The operating system is developed by the platform provider, or 'sponsor'[106], either alone or in cooperation with other firms. (b) The *application store* ('app store') serves as a digital distribution channel which allows consumers to browse and download apps directly to their mobile devices. Apps are available either free of charge or at a cost. The revenues are shared between the developer of the app and the operator of the app store, typically in a 70:30 ratio. Official application stores are controlled and operated by the platform provider, whereas other, independent app stores are run by network operators, handset manufacturers or software distributers.[107] The platform provider acts as the "ecosystem orchestrating keystone that creates and drives the value flow" (Tarnacha 2008, p. 225). Acting as a hub in the networked ecosystem, platform providers can influence, or even dictate, which

106 In case of alliances such as the *Symbian Foundation*, it designates the 'network management organization' (NMO).

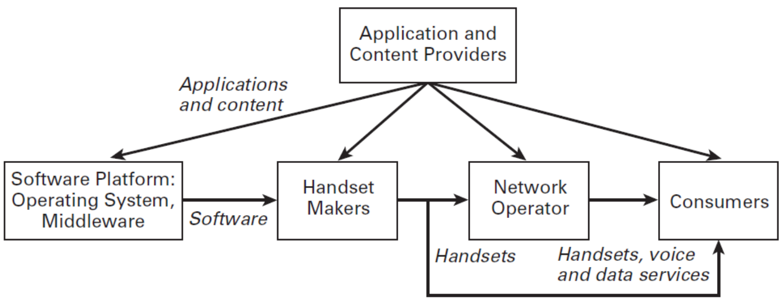
107 See WIP (2011) for a detailed market overview of 118 available app stores.

members can participate in the ecosystem, which products and services they are offering and at what conditions.

2. A base of loosely affiliated *application developers* provides compatible software for the smartphone platform. Apps are developed for one specific operating system and are incompatible with other devices. However, many app developers spend the effort to port their applications to multiple platforms, referred to as multi-platform development or multi-homing. App developers form a very heterogeneous group consisting of large-scale software companies, one-man corporations and even hobbyist developers.
3. *Consumers* use their smartphone devices, run by a particular smartphone operating system, to download compatible apps and other digital content, predominantly through the platform's official application store.
4. An alliance of *industry partners* support, foster and/or make use of the platform. Usually, an alliance consists of handset manufacturers, network operators, semiconductor companies, media publishers and prominent software partners.[108]

Figure 6-4 shows a typical smartphone ecosystem and the value flows. Please note that revenue streams run in the opposite direction.

Figure 6-4 **Example of a smartphone ecosystem**
(Source: Evans et al. 2006, p. 186, with minor changes)

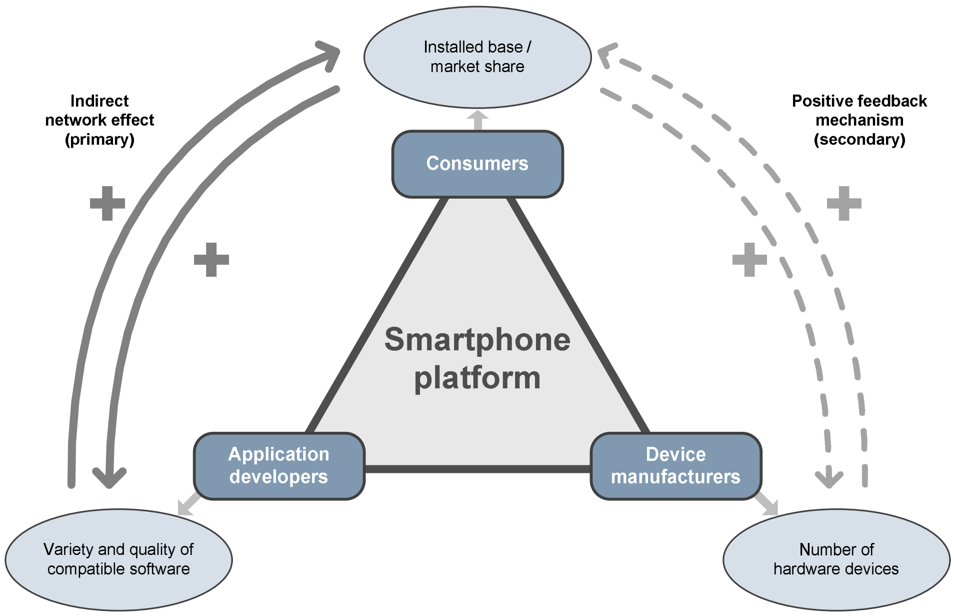


If we take the common example of vendor-independent ecosystems, such as *Google Android* or *Microsoft Windows Phone*, smartphone platforms give rise to positive feedback mechanisms

[108] The alliance component of a smartphone platform is only partly applicable to vendor-exclusive operating systems, used for instance by the *Apple iPhone* or *RIM's BlackBerry* devices. In these cases, the provider of the operating system is also the device manufacturer.

between applications developers, consumers and device manufacturers (Evans et al. 2006). Figure 6-5 illustrates such a simplified smartphone ecosystem and the inherent feedback processes.

Figure 6-5 **A stylized three-sided smartphone platform and its positive feedback mechanisms**



Consumers are attracted by smartphone platforms which are supported by a rich collection of third party applications. Hence, the larger the number of available apps, and the better their quality, the higher the market share of a platform. In turn, application developers favor smartphone platforms with high market shares as this offers a larger potential customer base for their apps. Putting these two causal relationships together reveals the inherent increasing returns logic: a high market share results in more apps being developed, which makes the platform even more successful with consumers. Heuser (2011, translation by the author) describes this increasing returns mechanism for example for the *iPhone*: "The more people have an iPhone, the more profitable it becomes to develop software applications for it — and each of those 'apps' increases the benefit of the iPhone for its users". Depicted on the left-hand side of Figure 6-5, this primary indirect network effect is the main driver for competition in the smartphone industry.

As the third influential actor, handset makers moderate between consumers and their chosen smartphone platforms (Lin & Ye 2009). Consumers cannot independently choose the hardware and the software components of their smartphone. Instead, each smartphone model is tightly bundled with a pre-installed operating system which cannot be replaced by a different operating system. Therefore, a consumer's *platform choice* more precisely refers to the choice of a *smartphone device* that runs with a particular *software platform*. This highlights the moderating role of handset manufacturers. Handset manufacturers equip their devices with operating systems that they expect to provide the highest benefit to their customers. Hence, the higher the acceptance of the platform in the marketplace, the larger the supply of devices that run this particular software platform. In turn, a larger number of devices to choose from for any particular platform will attract more consumers to this platform. This leads to a secondary positive feedback mechanism, depicted on the right-hand side of Figure 6-5: a high market share results in more devices being introduced which are based on this operating system, which in turn makes the platform even more popular with consumers.

In conclusion, a smartphone's software platform is located at the heart of a complex relationship between consumers, software developers and handset manufacturers. The platform provider needs to "nurture" all sides to establish a successful platform (Evans et al. 2006, p. 63).

6.3 The current competitive landscape in the smartphone industry

Despite the significance of the smartphone industry, a comprehensive historical overview is still lacking in the literature. In order to address this gap, Appendix A elaborates the development of the smartphone industry based on a systematic press analysis from January 2000 to March 2011. In the following, I summarize the historical account by focusing on major milestones and discussing today's competitive situation.

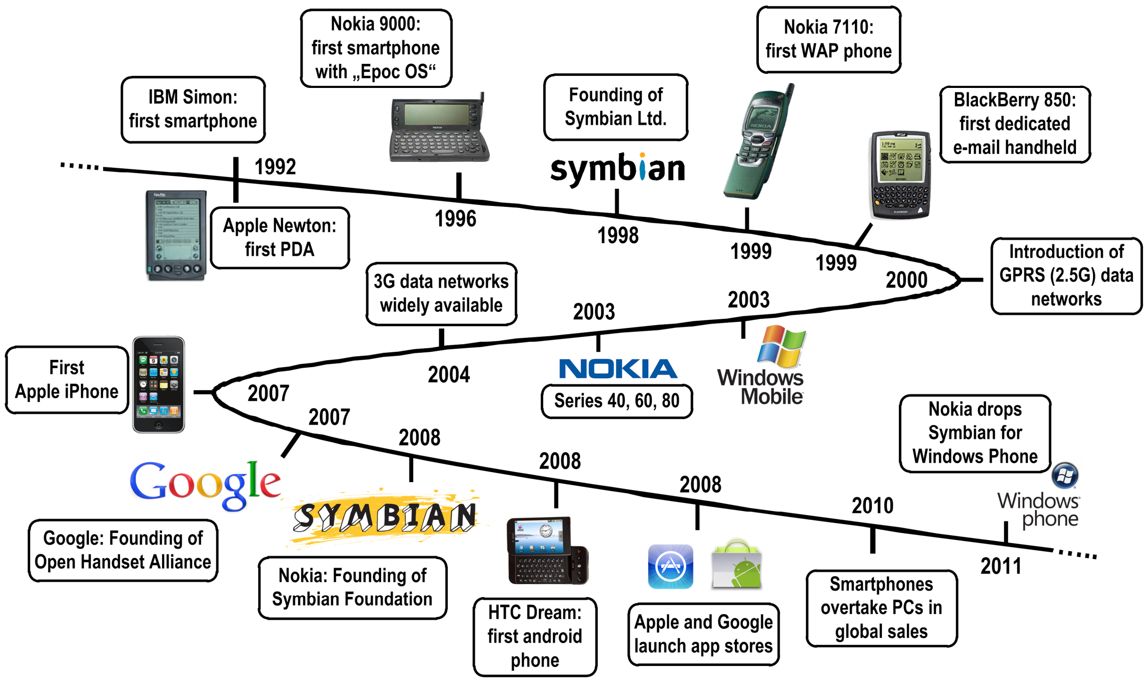
The rise of the smartphone industry since the 1990s is closely connected with the ongoing process of *convergence*. This term describes the integration of infrastructures, services and devices in the information, telecommunication and media industries (Storsul & Fagerjord 2008). Convergence is driven by *digitization*, which is defined as the "conversion of analog information into digital information" (Webster's Dictionary, 11th edition). In the last two decades, virtually all media, information and communication technologies have gone through a phase of digitization. Digital music replaced records and tapes, and printed works such as books and newspapers are increasingly provided in digital formats. Just as mobile and fixed-line telephony, television and radio became digitized in many countries. Equally, photos and videos are now also produced and distributed digitally. This digitization process has led to a *network convergence*: sound, text and images are all transmitted as bits and bytes in digital networks.

Likewise, digitization has facilitated the process of *terminal convergence*, which describes the integration of previously independent device categories into a single product (Storsul & Fagerjord 2008). Hence, smartphones constitute a prime example for a *converged device*. In addition to the traditional mobile phone features, they combine PC functionality, mobile internet connectivity and email, music and video playback as well as camera and GPS capabilities. By integrating previously separated technologies, smartphones provide a myriad of functions in a single device. From an economic perspective, this process of technological convergence drives the *convergence of markets*. Industry boundaries blur as the distinction between telecom markets and media markets becomes more and more impractical. As a result, traditional mobile phone manufacturers, such as *Nokia,* now compete head-to-head with former computer companies, such as *Apple*, and internet and software firms, such as *Google* and *Microsoft*.

The origins of the smartphone industry date back to the *IBM Simon* from 1992 and the *Nokia Communicator* launched in 1996 (Evans et al. 2006). Figure 6-6 provides a brief summary of the historical development by illustrating important milestones in the evolution of the smartphone industry.[109]

[109] Despite the significance of the industry from today's perspective, a comprehensive historical overview is still lacking in the literature. In order to address this gap, Appendix A elaborates in detail on the historical development of the smartphone industry based on a systematic press analysis and a literature review.

Figure 6-6 **Historical milestones in the evolution of the smartphone industry**

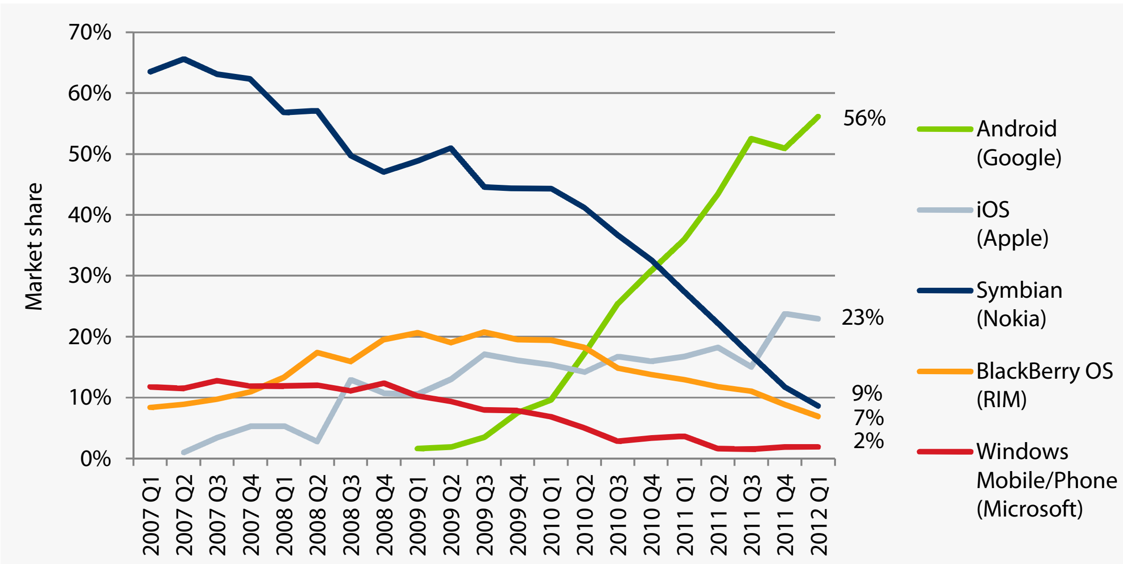


The year 2007 marked a landmark for the mobile communication industry. *Apple*'s announcement of the first *iPhone* in January (Apple 2007a) and the launch of the product in June (Apple 2007b) attracted enormous media attention and pushed the smartphone technology forward in terms of functionality and user-friendly design. The markets reacted strongly to the success of the *iPhone* (Apple 2007c), and competitors were pressured to catch up with what was perceived as the benchmark device for the whole industry. The internet company *Google* responded by launching the *Android* smartphone platform at the end of 2007 (Google 2007). This platform was accompanied by an industry consortium, the *Open Handset Alliance*, "a multinational alliance of technology and mobile industry leaders" (Google 2007). It comprises network operators, device manufacturers, chip makers, software companies and others who cooperate to provide a royalty-free, open-source smartphone platform, although it is still strongly dominated by *Google*.

While newcomers *Apple* and *Google* quickly gained market share, other manufacturers, most importantly *Palm*, *RIM (BlackBerry)* and the global market leader *Nokia*, struggled with the new competition, particularly in terms of technical capabilities and design (Wendel 2008, p. 4). Faced with continuous market share losses, *Nokia*'s CEO Stephen Elop used strong words to describe *Nokia*'s miserable situation in the smartphone industry: "We are standing on a burning platform" (Elop 2011). By this, Elop was referring to the fierce competition from *Apple* and *Google* which had caused *Nokia*'s drastic drop in market share. The phone business had become a software business, and Nokia had failed to establish a successful ecosystem around its *Symbian* platform. As part of a large-scale corporate restructuring, *Nokia* decided to quit *Symbian* and to partner with *Microsoft* in order to "compete in the war of ecosystems" (Elop 2011). However, industry experts were rather skeptical that "two wrongs could make a right" (Noyes 2011), given that *Microsoft* has also failed to successfully compete in the smartphone industry for a long time. *RIM*, once a forerunner in the industry with its messaging-oriented *BlackBerry* smartphones, has also struggled and faces an uncertain future (Lambrecht 2011; Simon & Taylor 2012).

To illustrate the fierce platform competition in the smartphone industry, Figure Figure 6-7 shows the quarterly market shares of the major smartphone platforms between 2007 and the first quarter of 2012.

Figure 6-7 **Market share of major smartphone platforms 2007-2012**
(Data source: Gartner 2008a, 2008b, 2008c, 2009, 2010b, 2010c, 2010e, 2011b, 2011c, 2011d, 2011e, 2012a; 2012b; own calculations)



As of the beginning of 2012, *Apple* and *Google* clearly dominate the market. However, the outcome of the platform competition in this highly dynamic industry remains open. Global industry alliances have been formed to counter one another, while open-source and proprietary system platforms are competing in a second arena of competition. One thing seems certain:

smartphones will continue to see rapid growth and a further increase in their impact on the global mobile communications industry. For both consumers and the rest of the mobile world, the outcome of the platform competition has serious consequences. What will be the power balance between software developers, network operators, handset manufacturers, media publishers and platform providers? Who will receive the advertising revenues generated on smartphones, and who will claim ownership of the valuable customer data in the light of privacy concerns (Auletta 2009, p. 210)? And ultimately: Which platform, if any, will dominate the smartphone market? Considering the debate on path dependence in the PC industry and its social and economic consequences, platform competition in the smartphone industry is a highly interesting and relevant case: "the stakes are huge, as the mobile computing market could prove to be larger than the PC market ever was" (Helft 2010).

The proposed simulation model aims to provide new theoretical insights to better understand technological path dependence for these types of two-sided markets. The present chapter has been devoted to the smartphone industry, which will serve as one example application of the generic simulation model, which has already been described in chapter 5. The following chapter will now elaborate on the model validation and calibration on the basis of the selected empirical case.

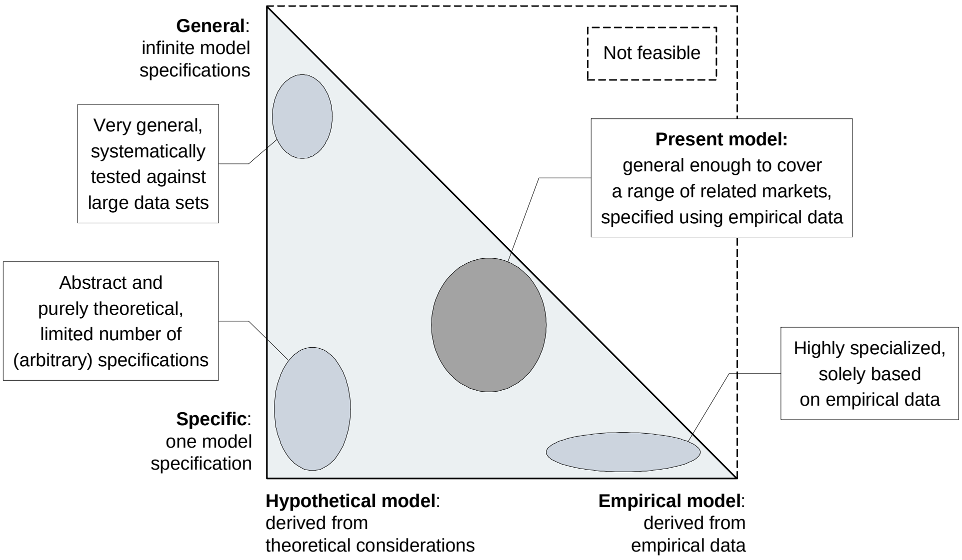
7 Model validation and calibration: empirical evidence from the smartphone industry

The ultimate aim of simulation, as with research in general, is to "learn something about the underlying dynamics that drive the real world" (Brenner & Werker 2007, p. 231). It is thus deserved that the *empirical* validation of simulation models has received great attention in recent years (Fagiolo et al. 2007). Empirical validation can take place at different levels (Garcia 2007; Law 2007). At the micro level, it addresses whether the building blocks of the model, i.e., the agents' behavior and decision heuristics, are build on empirically sound assumptions. At the macro level, the empirical validation compares the simulation output with empirical data collected from the real-world target. Focusing on the micro level, this chapter elaborates on the role of empirical data for the model design and explains the micro-validation and calibration process.

Simulation in the social sciences comprises a multitude of theoretically and empirically informed models. At the one extreme, purely theoretical, "empirically distant approaches" (Davis et al. 2007, p. 480) are used, for instance NK-models which try to represent organizational strategies with abstract '0' and '1' bit strings. At the opposite extreme, highly specific empirical models address particular use cases and are built on detailed empirical observations and data, but often lack theoretical grounding and generalizability. Figure 7-1 classifies the different types of simulation approaches based on two dimensions: the degree of generalization (general vs. specific) and the source of model assumptions (theoretical considerations vs. empirical data).[110]

[110] Please refer to Brenner & Werker (2007) for a more detailed description of their classification scheme, including examples for each typology. See also Boero & Squazzoni (2005) who distinguish between "case-based models", "typifications" and "theoretical abstractions".

Figure 7-1 **Classification of simulation models in the social sciences**
Adapted from Brenner & Werker (2007, p. 231)



With respect to the horizontal dimension, the proposed model takes an intermediate position. It is guided by theoretical considerations on technological path dependence and network effects. Likewise, the model design is informed by 'stylized facts' drawn from empirical examples of the "hardware/software paradigm" (Katz & Shapiro 1985) such as personal computers, home video systems and smartphones. Therefore, the model is applicable to a collection of related and clearly demarcated economic processes: cases of platform competition in two-sided markets with indirect network effects.

Whenever a model is general in the sense that it captures different kinds of systems, there is a set of possible model specifications, each of which "represents one specific choice of parameters and premises" (Werker & Brenner 2004, p. 9). Against that background, the higher explanatory power of the empirically informed model comes at a cost: due to its greater realism in comparison to abstract theoretical models, any agent-based model with "realistic assumptions and agent descriptions invariably contains many degrees of freedom [i.e. number of parameters/model specifications]" (Fagiolo et al. 2007, p. 220). Hence, given the large number of model parameters that are necessary to build a reasonably realistic model of competition in two-sided markets, it is impossible to fully explore the multidimensional parameter space by varying all parameters at the same time.[111] However, simply fixing some of the model parameters to arbitrary values would raise serious questions about the validity of the results.

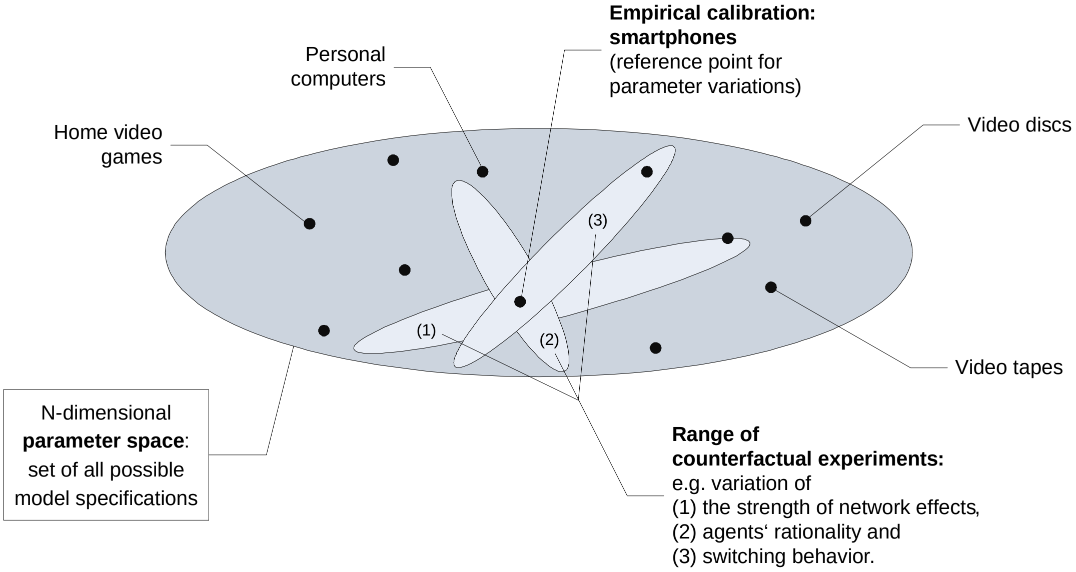
In order to mitigate this problem, model parameter values can be set on the basis of sound empirical data. In this way, empirical evidence serves to "restrict the degrees of freedom by directly calibrating initial conditions and/or parameters", thus reducing the "space of possible 'worlds' that are explored" (Fagiolo et al. 2007, p. 220/206). However, a full calibration approach, in which all parameters are fixed to their empirically calibrated values, would mean analyzing only one model specification. As a result, no conclusions could be drawn on the effect of changing model parameters for the emergence of technological path dependence.

The solution is to combine the empirical model calibration with parameter variation experiments. Among the various industries to which the proposed model could be applied, the global smartphone industry was chosen to provide empirical evidence. On the basis of the empirical calibration, *counterfactual experiments* are then conducted to address 'what-if' scenarios for this particular industry: for instance, what would the (modeled) smartphone industry look like *if* indirect network effects were stronger, or *if* switching costs were lower? The aim of this approach is to explore the causal relationships between the independent variables and the model behavior by analyzing counterfactual sets of parameter values. As Dubé et al. (2010, p. 216) note, "constructing a counterfactual market outcome using a field experiment would be highly impractical". In contrast, simulation research allows us to conduct 'virtual' experiments based on empirically calibrated parameters in combination with counterfactual parameter settings.

Figure 7-2 visualizes the set of possible model specifications for the proposed model and shows how counterfactual experiments for the smartphone industry explore a subset of the whole parameter space, which consists of all possible empirical settings the model can capture.

111 The setup of the factorial design (section 8.2) discusses this issue in more detail.

Figure 7-2 **Model specifications: empirical calibration and counterfactual experiments**
Adapted from Werker & Brenner (2004, p. 9)



Although the generic model can be employed for different instances of the 'hardware/software paradigm', for instance the *VHS/Betamax* case[112], here the application is deliberately restricted to the smartphone industry. The objective is to *intentionally* reduce the generality of the simulation, thereby limiting the large set of model specifications that need to be run to explore the model behavior.[113] However, the model does not rely on a single, empirically calibrated model specification. Instead, counterfactual experiments that vary certain dimensions (parameters) of the model are conducted to explore a counterfactual world, representing a subset of the whole parameter space. In conclusion, by using the smartphone industry as a reference point for a range of counterfactual scenarios, the simulation aims to discover the causal relationships between the independent variables and the emergence of technological lock-ins.

112 Table 5-1 addresses a number of other possible applications for the model.

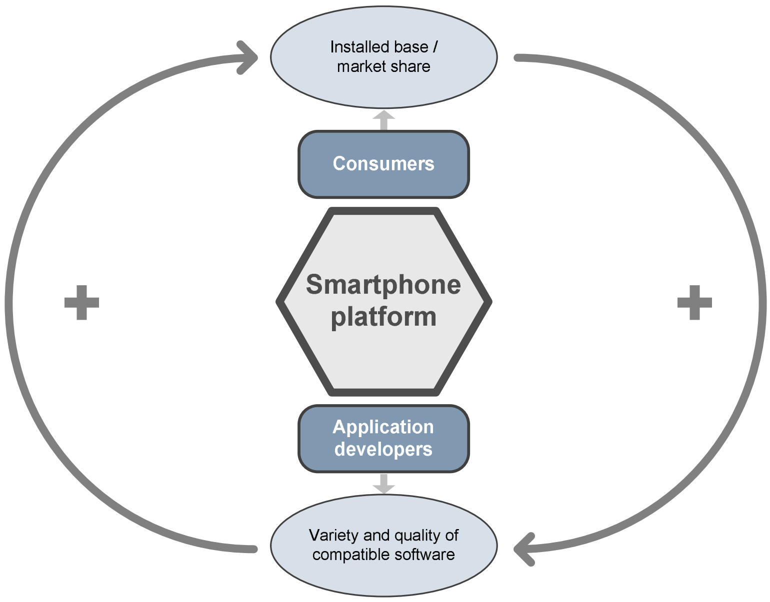
113 Harrison et al. rightly note that "simulation findings are only demonstrated for the region of parameter space examined experimentally" (Harrison et al. 2007, p. 1243). Nevertheless, this limitation is regarded as a 'small price to pay' in light of the benefits of the more realistic but inevitably complex model. The external validity of the results will be discussed in more detail in chapter 9.

7.1 Applicability of the model to the empirical case

Prior to the calibration of the model parameters, I briefly discuss the applicability of the generic model to the specific empirical case by addressing the role of device manufacturers and pricing in the smartphone industry.

As discussed in chapter 6, a smartphone platform is at the heart of a complex relationship between device manufacturers, software application providers and consumers. Accordingly, a smartphone ecosystem was described as being governed by a three-sided platform. However, the industry can be reasonably represented by a two-sided market model (see Figure 7-3) by disregarding the role of device manufacturers.

Figure 7-3 **A stylized two-sided smartphone platform and its positive feedback mechanisms**



The argument in favor of this abstraction is twofold. First, the industry analysis gave no indication that the role of device manufacturers is crucial for the success of a platform. Device manufacturers offer smartphones with the operating systems that are demanded by consumers, and device manufacturers have been shown to correct unsuccessful platform strategies. For instance, the *Symbian* platform became technically inferior in comparison to other platforms and thus began losing market share (Parker 2010). As a result, *Sony Ericsson* stopped offering phones that ran *Symbian* and abandoned the *Symbian* platform completely in September 2010. Second, the inclusion of device manufacturers into the model would mean further differentiating between vendor-specific (*Apple*, *RIM*) and open platforms (*Google*, *Symbian, Microsoft*), which would make the model more complex. In the context of the research question, it is believed that the benefit of a more accurate representation of the industry does not justify the higher level of model complexity.

Regarding the role of pricing, empirical evidence revealed that differences in pricing strategies can be neglected for the case of platform competition in the smartphone industry. Therefore, the model abstracts from any pricing issues by assuming that pricing differences are either insignificant or that all platforms are priced at the same level. The industry analysis showed that the open platforms (*Google*, *Symbian*) provide their operating systems free of charge to both device manufacturers and software developers. Concerning the proprietary operating systems (e.g., *Windows Mobile* or former *Symbian* versions), licensing costs can be considered insignificant in relation to the total bill of materials for a modern smartphone. Furthermore, in contrast to PC operating systems that are sold independently of the hardware by retailers, smartphone users do not have contact with the pricing of the software platform. Regarding the developers of mobile apps, the pricing strategies of the platforms' official app stores are almost identical in terms of revenue share agreements, joining fees and submission fees. In summary, platform pricing in the smartphone industry has a negligible impact on consumers' and developers' decisions and can be safely disregarded in the model.

7.2 Data requirements and data sources

The simulation model, which was presented in detail in chapter 5, incorporates three main entities: (1) competing platforms, (2) user agents and (3) complementor agents. For the envisaged empirical calibration, the properties and the behavior of these entities (represented by the model parameters listed in Table 5-3) are to be configured based on empirical data for the smartphone industry.

In particular, empirical evidence is required for:

- the innovation diffusion process, notably the speed of adoption and the shape of the Bass diffusion curve for smartphones;
- the strength of the indirect network effect, i.e., the relative importance of apps;

- the information search and decision-making behavior of smartphone buyers;
- the decision-making heuristics of app developers when deciding on a smartphone platform;
- the extent of multi-homing, i.e., the ease of multi-platform support by developers;
- the switching behavior of both end users and developers.

Model calibration is performed on the basis of quantitative and qualitative empirical evidence for the smartphone industry. The main data sources are a computer-based survey with N=240 students to estimate consumers' utility function for smartphones and analyze their information search and decision-making behavior. Moreover, semi-structured interviews were conducted with application developers (the 'complementors' in terms of the model) in order to model their decision heuristics for platform choice. For this purpose, my colleague and I attended four international industry conferences between autumn 2009 and summer 2010.

7.3 Innovation diffusion

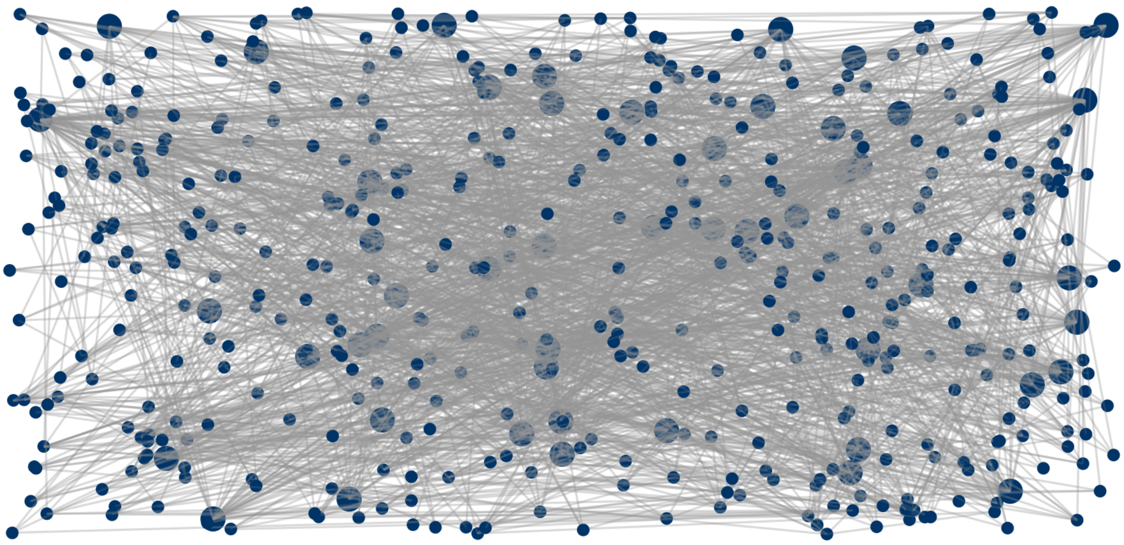
This section describes the empirical calibration of the Bass diffusion curve that is used to model the innovation adoption behavior of agents in the simulation model. Cumulative sales of an innovative durable product, such as smartphones, generally follow an S-shaped curve, represented in the simulation model by an agent-based adaptation of the classic Bass diffusion model.[114] The empirical calibration serves to determine the exact shape of the S-shaped diffusion curve that will be used for the simulation.

It has been argued that the network topology has a crucial impact on the diffusion process. For that reason, I use recent empirical evidence by Dover et al. (2012) regarding the structure of real-world influence networks. The scale-free network parameter m (Barabási & Albert 1999), equal to the model parameter D^{m}, is set to the minimum value of five influence networks analyzed by Dover et al. (2012, see their appendix). On this basis, the minimum number of links for a user agent is set to $D^{m} = 4$. The simulation is run with 500 user agents

[114] For details, please refer to section 5.1.2.2.1.

(U = 500).[115] The resulting scale-free network structure of the model is depicted in Figure 7-4. Hub agents, defined as the 10 percent of agents with the highest number of links, are indicated by larger diameters.

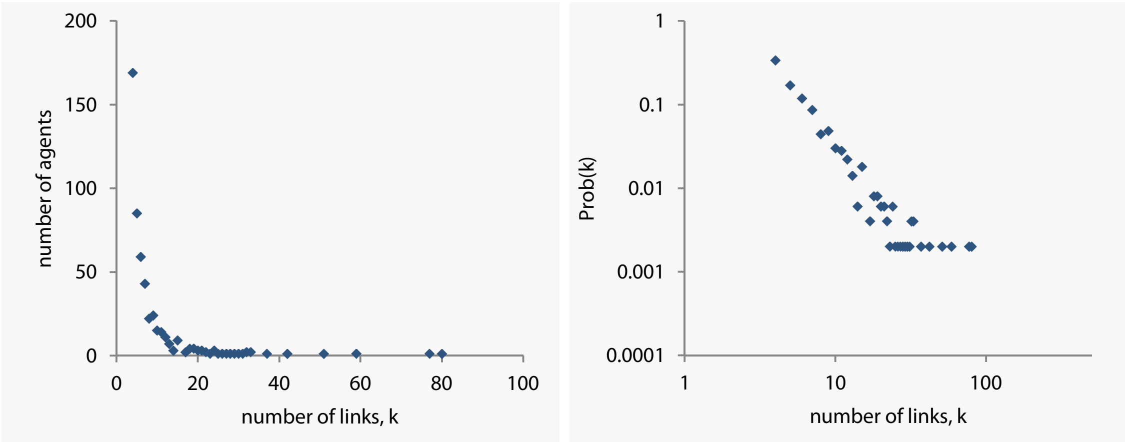
Figure 7-4 **Simulated scale-free social network**
U = 500, D^{m} = 4; one sample



In addition, Figure 7-5 shows the degree distribution of the simulated scale-free network. As can be seen, it follows a power law as a result of the preferential attachment mechanism.

115 The number of agents that can be modeled on a computer system is limited by performance constraints. A consumer population of 500 agents is believed to provide reliable results (Garcia 2005). Furthermore, this parameter setting will be later verified in a robustness check, which is described in section 8.11.

Figure 7-5 **Degree distribution of the simulated scale-free social network**
$U = 500, D^{m} = 4$; one sample; left figure in linear scale, right figure in log scale



In order to model the innovation adoption process, the underlying logic of the Bass diffusion model in its differential-equation form is carried over into an agent-based approach. The simulation adoption process is calibrated using empirical diffusion data for mobile phones.

Various approaches can be used to forecast diffusion patterns of innovations using the Bass model (cf. Lilien & Rangaswamy 1998, pp. 199-202). The Bass model parameters p, q and M can be estimated using linear or non-linear regression when there is data available for a sufficient number of years. Another approach that is often successfully applied in practice is to identify previous technologies that are comparable with the current one. In this approach, the Bass coefficients p and q are determined from historical sales trajectories of predecessor technologies and are used as best estimates for forecasting the adoption of the new innovation. For the purpose of model calibration, the latter approach is chosen.[116] The historical diffusion trajectory of wireless communications, i.e., the introduction of mobile phones, is assumed to adequately forecast the diffusion of smartphones.

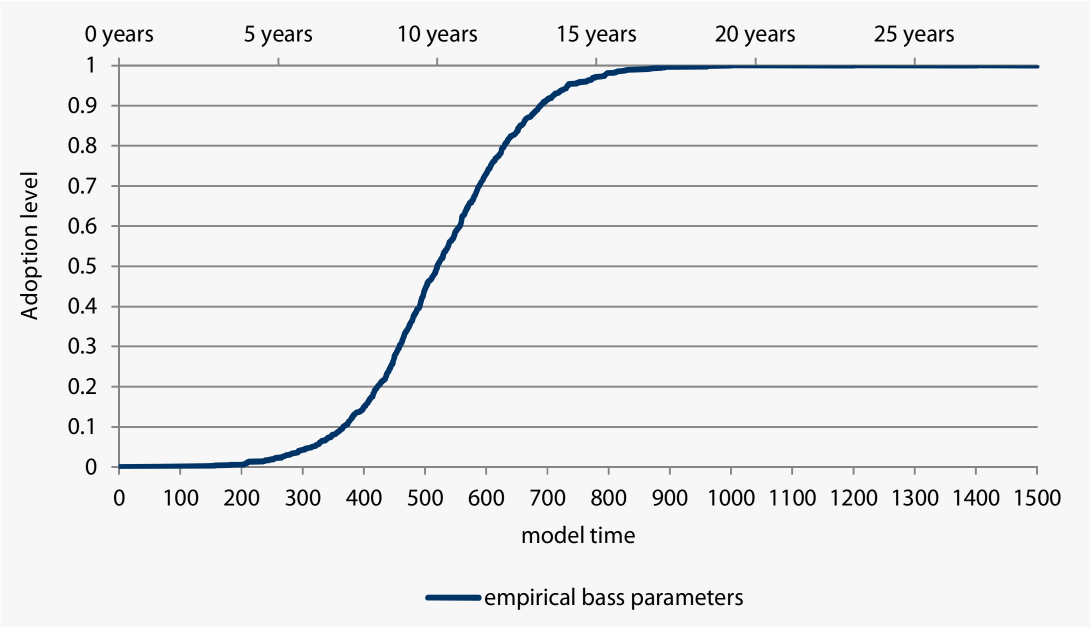
Sundqvist et al. (2005) employ the Bass model using nonlinear least squares (NLS) estimation with annual data on wireless subscribers for 64 countries since 1981.[117] I rely on their parameter estimates ($p = .00076, q = .68$) for model calibration. Figure 7-6 depicts the diffusion

116 Estimating the Bass model using smartphone adoption data is not possible at the time of writing, given that the peak in adoption has most likely not yet been reached.

117 Data is provided by the World Cellular Information Service (WCIS), previously known as the EMC database.

trajectory for wireless communications as estimated by Sundqvist et al. (2005). The two horizontal axes measure the time in years (top) and the equivalent model time (bottom), where one model time step is equivalent to a week in physical time.

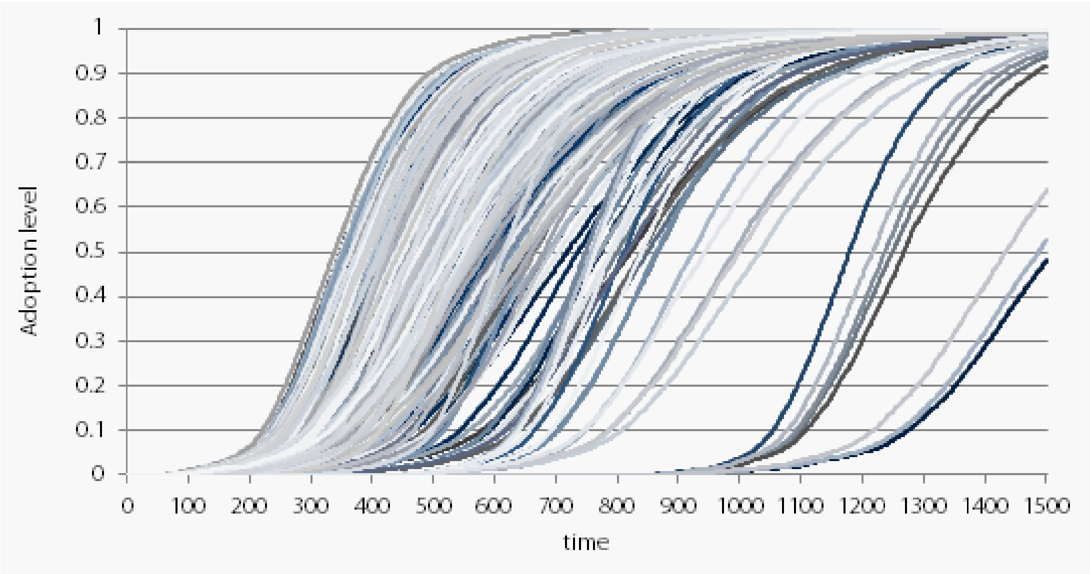
Figure 7-6 **Diffusion trajectory of wireless communications**
64 countries average; data source: Sundqvist et al. (2005) / EMC database



The diffusion process for wireless communications took about 17 years to complete. Penetration reached 50 percent of the population after approximately 10 years, which was also the period with the highest rate of adoption. The same diffusion curve is now assumed for modeling the adoption of smartphones. In the simulation model, D^{ext} relates to the Bass model coefficient of external influence p, and D^{wom} to the word-of-mouth Bass model coefficient q. However, the Bass model coefficients estimated by Sundqvist et al. cannot be directly employed for the simulation model, because although the model parameters represent the same underlying concepts, the logic of the micro-modeling approach is fundamentally different from the differential-equation form. The solution is to undertake a simulation experiment to estimate the model parameters D^{ext} and D^{wom} that replicate the empirical findings as accurately as possible. For this purpose, an optimization experiment is carried out. First, a suitable value range for both model parameters is narrowed down using an iterative approach. Based on a visual inspection of the diffusion curves for various high/low combinations, the total parameter space is limited to values between 5×10^{-7} and 1×10^{-5} for D^{ext} and to values between 0.0125 and 0.0275 for D^{wom}.

In a second step, a curve-fitting experiment is conducted to find the optimal solution in the parameter space. A total of 620 parameter sets are tested, using 20 factor levels for D^{ext} (in steps of 5×10^{-7}) and 31 factor levels for D^{wom} (in steps of 5×10^{-4}). Figure 7-7 presents the experimental results from the curve-fitting experiment, showing the resulting set of S-shaped diffusion curves.

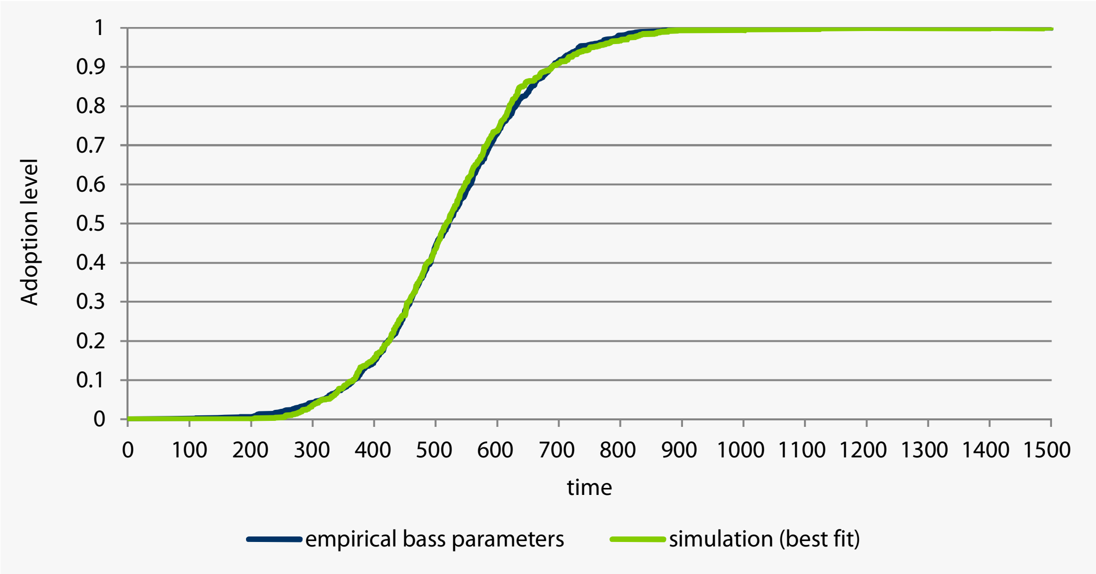
Figure 7-7 **Curve fitting experiment to calibrate the agent-based diffusion model**
Result of 620 parameter sets: 20 factor levels for D^{ext}, 31 factor levels for D^{wom}



Based on this data, the aim is to find the simulated diffusion curve that best fits the historical diffusion trajectory of wireless communications. For that purpose, I identify the optimal parameter set which produces the highest goodness-of-fit score in terms of R-squared measures (Hair et al. 1998) of the *simulated* diffusion pattern to the *empirical* diffusion pattern estimated by Sundqvist et al. (2005). The optimal solution is $D^{ext} = 4 \times 10^{-6}$ and $D^{wom} = 0.025$, yielding a maximum R^2-value of 0.9996.[118] This R^2-value very close to 1 indicates an almost perfect fit to the empirical diffusion curve, as can be seen in Figure 7-8.

118 The average R^2-value of the 620 tested parameter sets is 0.57.

Figure 7-8 **Simulated diffusion curve vs. empirical diffusion curve**
$D^{ext} = 4 \times 10^{-6}$; $D^{wom} = 0.025$; Goodness-of-fit score $R^2 = 0.9996$



To conclude, the agent-based diffusion model is able to fully replicate the empirical diffusion trajectory for wireless communications as estimated by Sundqvist et al. (2005).[119] Furthermore, these finding indicate that the chosen micro-modeling approach embodied in the proposed agent-based model is a good approximation for the Bass model in general.

In the simulation model, adoption takes off after roughly 200 time steps. The diffusion of smartphones reaches 50 percent of the population after approximately 500 model time steps. After 900 time steps, virtually every agent has adopted the innovation. To account for platform competition *after* the innovation has diffused completely, the maximum number of model time steps is set to $T = 1300$, which equals a tme coverage of 25 years.

7.4 Users: evidence from a consumer survey

This subchapter discusses the magnitude of the indirect network effect in the smartphone industry, which will serve as one input parameter for the simulation model. Furthermore,

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119 As discussed, it is assumed that the diffusion of smartphones follows the same trajectory as the predecessor technology. This is a typical auxiliary assumption used when the diffusion data for the current innovation is insufficient to estimate the model (Lilien & Rangaswamy 1998). Therefore, the derived diffusion curve could be replaced by an improved model when there are more data points available.

empirical research is used to gain further insight into the information search and decision-making behavior of smartphone buyers, which also enhances the empirical calibration of the user agents' behavior in the simulation model. For these purposes, a computer-based survey with N=240 students was conducted. Corresponding to the model parameters, the survey incorporates items on consumers' information search behavior and preference formation. Furthermore, the survey provides empirical evidence for consumers' rationality level and includes various other items such as the prevalence of smartphone ownership, platform choice and consumer satisfaction.

The survey was carried out in close cooperation with fellow colleague Alexandra Langer. In her dissertation, she analyzes individual decision-making as a driver for consumer path dependence (Langer 2011). Because of our joint focus on the smartphone industry, I combined my questionnaire with her experimental study.

We attracted a total of 240 students from the *School of Business and Economics* at *Freie Universität Berlin* as subjects for our study. It was announced as a 'scientific marketing study' without any reference to the smartphone industry in order to minimize selection bias (Groves et al. 2004). All students volunteered to participate and were compensated with a modest amount of money for their time and effort.[120] We undertook a "declared pretest" (de Vaus 2002, p. 116) with 13 students and eight PhD students to determine the effectiveness of our survey questionnaire. During the pretest we discussed question meaning, order, wording and task difficulty with the participants. Based on their feedback, we reworked parts of the survey structure and rephrased items which were initially described as ambiguous by some participants. Changes to my part of the survey were later verified through a second pretest with 23 students. The pretests also served to test the time requirements of the study and to guarantee that the technical setup worked correctly. The computer-based survey took place in a computer lab on the campus of the *Freie Universität Berlin* and participants were constantly monitored by a supervisor. The respondents were briefly introduced to the study to clarify any concerns or questions. However, the nature of our research projects, including the research questions, was deliberately not revealed in order not to influence the response behavior (Groves et al. 2004). In

120 Financial support for the undertaking from *Deutsche Forschungsgemeinschaft (DFG)* is gratefully acknowledged.

total, the survey took about 50 minutes to complete. We used *LimeSurvey*[121], a powerful free and open-source survey application, to implement and run the survey. The software itself is self-guiding for the respondents. The online survey was hosted on a webserver at *ZEDAT*, the university's central computer service, and the survey results were stored in a relational database (*MySQL*) for further analysis.

Table 7-1 shows the schedule of the pretests and actual survey sessions, which took place between May and July 2010.

Table 7-1 **Time schedule of the pretest and survey sessions**

Date	*Number of participants*	*Comments*
26.05.2010	13 students + 8 PhD students	Pre-test 1
16.06.2010	23 students	Pre-test 2
08.07.2010	29 students	Survey session 1
09.07.2010	26 students	Survey session 2
09.07.2010	20 students	Survey session 3
12.07.2010	26 students	Survey session 4
12.07.2010	26 students	Survey session 5
13.07.2010	24 students	Survey session 6
13.07.2010	24 students	Survey session 7
15.07.2010	29 students	Survey session 8
	240 students (incl. pre-tests) / 204 students (excl. pre-tests)	

The survey yielded a total number of 204 cases, excluding the two pretests. Incomplete records (N=4) were removed. The dataset was then screened for errors before the analysis phase. In general, data errors were not a major problem. By using a computer-based method, we were able to rule out transfer errors from paper to the computer file and to minimize response scores that were out of range. Furthermore, we used conditions for questions depending on earlier answers

121 *LimeSurvey* is extensively used by academic institutions, governments as well as private companies to run computer-based question-and-answer surveys. The software is written in *PHP* and distributed under the *GNU General Public License*. The latest version (currently 1.9) of the open source online survey application can be found at http://www.limesurvey.org.

('skip logic'/'branching'), thus minimizing effort for the participants. Please refer to Appendix A for screenshots of the consumer survey.

For control variables, we included items on the respondents' age, sex, country of origin, interest in technology, smartphone ownership and their average monthly mobile phone bill. More details on the control variables and the response analysis are provided by Langer (2011, pp. 70-79, 94-95) and are omitted here for brevity. Obviously, the student respondents of the survey are not a representative sample of smartphone users, which may reduce the generalizability of the conclusions.[122] However, student samples are widely used for practical reasons, not only in consumer research. Furthermore, students are a typical target audience for consumer electronics such as smartphones and have a clear influence on the emergence of the industry. Hence, it is believed that external validity concerns due to the student sample can be largely ignored for the present study.

For data screening, categorical variables such as *sex* were double-checked for errors using histograms for each of the variables in order to detect responses not within the range of possible scores. Continuous variables such as *age* where checked for errors using descriptive statistics such as the minimum and maximum values. Both procedures revealed only one out-of-range error (N=1), and the corresponding record was excluded from the dataset. Thus, a total of N=199 cases remained for statistical analysis after screening and cleaning the data.

7.4.1 Information search

In order to investigate consumers' information search behavior, the following items were included in the survey (see Table 7-2).

[122] Two recent and very interesting papers address this general issue: Henry (2008) raises meta-theoretical concerns about the continued use of student samples. Henrich et al. (2010) provide compelling evidence that members of Western, Educated, Industrialized, Rich, and Democratic (WEIRD) societies are among the least representative populations for addressing questions of *human* nature.

Table 7-2 Items related to the information search behavior

Item ID	Wording	Response format
OW	*Do you own a smartphone?*	Binary (yes/no)
OS	*When I consider buying a smartphone, I ask other people for advice.*	7-point Likert (1=disagree strongly, 7=agree strongly)
LI	*About how many people have you talked to about the choice of a smartphone before you decided on a particular model?*	Numeric (0-100)
RC	*In general, would you recommend your smartphone to others?*	Binary (yes/no)
CS1	*Have you considered any smartphones with other operating systems than the one you chose?*	Binary (yes/no)
CS2 – C7	*If yes: Please choose which operating systems you have considered in your purchasing decision:* *Apple iPhone iOS* *Google Android* *Symbian OS* *Windows Mobile* *BlackBerry OS* *- Other -*	Binary (yes/no) Respondents can select all options that apply.

Due to a late change in the composition of items after the first survey round, the dataset was reduced by 29 cases, resulting in a total of N=170 cases. In the sample, 46 respondents (27.1%) report owning a smartphone, as opposed to 124 respondents (72.9%) that do not own a smartphone.[123] The other items apply only to smartphone owners. Therefore, the findings are based on a relatively small number of respondents (N=46) and the results should be used with caution.

Respondents tend to agree that they ask other people for advice when buying a smartphone (Mean=4.9, SD=1.3). On average, the respondents have talked to three other people about the choice of their smartphone. The responses are spread across a wide range (mean=3.11, SD=3.3), with four respondents reporting having talked to more than 10 other people. Thirty-six (78.3%) respondents would recommend their smartphone to others, as opposed to only ten (21.7%) who are dissatisfied. All in all, the survey confirms that interpersonal sources are crucial

123 These numbers from the student sample are comparable to the average smartphone penetration in Germany at the time of the study. For the year 2010, BITKOM (2010) reports that 21 percent of the mobile phones being used by subscribers are smartphones.

for the smartphone purchasing decision and that the model's focus on *positive* word of mouth is a reasonable assumption.

In order to estimate the size of the consideration set for smartphone choices, the survey employs a widely used item created by Gronhaug (1973). Respondents were asked to state which other types of smartphones they considered in their purchasing decision, apart from their current platform choice. The results show that 25 respondents (54.3%) did not consider *any* other platform, versus 21 (45.7%) who also selected a number of other platforms for their consideration set. Overall, the size of consumers' consideration set varies with a mean value of 1.85 and a standard deviation of 1.1. Given that there are currently five major smartphone platforms on the market (Gartner 2011b), consumers on average evaluate only two of them, equaling about 37 percent of the available options. This finding is consistent with recent empirical evidence on mobile phone purchases by Ding et al. (2010, p. 121), who report an average relative consideration set size of 29 percent.[124]

To conclude, the survey shows that consumers clearly do not evaluate all available smartphone platforms on the market when deciding on a device. Consumers possess limited information-processing abilities and hence do not make explicit utility comparisons across *all* available options (cf. Mehta et al. 2003). Based on the survey results discussed above, the information level parameter is set to $U^{\text{infolevel}} = 0.37$.

7.4.2 Preference formation: A conjoint analysis

The magnitude of increasing returns is a prominent influencing factor which was mentioned in the earliest contributions on technological path dependence, for instance in Arthur's seminal model (Arthur 1989). In the proposed simulation model, it is represented by the strength of the indirect network effect. This section describes the empirical calibration of this parameter for the smartphone industry on the basis of a conjoint analysis.

In the model, users evaluate platforms on two dimensions: (1) the *inherent value*, or 'quality', of the platform, and (2) the *network value* from the availability of complementary products. Looking specifically at smartphones, a consumer survey by Goldman Sachs (2009)

124 See also Hauser & Wernerfelt (1990) for a meta-study on consideration set sizes for various product categories.

provides empirical evidence on which product attributes are essential parts of the value proposition to smartphones users. Table 7-3 summarizes the findings and relates the identified product attributes to the proposed model.

Table 7-3 **Product attributes of smartphones**
Source: Smartphone survey by Goldman Sachs (2009)

Product attribute (Goldman Sachs survey)	*Category*	*Model terminology*
▪ Operating system / user interface ▪ Email capability ▪ Browser capability	Software platform	Inherent value, ‘quality’ of the platform
▪ Available applications	Apps	Network value, availability of complementary products
▪ Handset design ▪ Physical keyboard ▪ Price ▪ Touchscreen	Device	(Not incorporated in the model)

The platform-specific attributes corresponding to the first two categories are represented in the model by the inherent value and the network value of a platform. Device-specific attributes, however, are not incorporated and treated as random influences in the model. This decision is justified by the fact that handset design, form factor and hardware quality are completely independent of the underlying smartphone platform. Moreover, technological advances quickly spread to new devices, regardless of their platform.[125]

Regarding the inherent value and the network value of a smartphone platform, the empirical calibration addresses a number of issues in order to ensure a realistic representation of consumers’ preference structure in the simulation model:

- In terms of utility, how ‘good’ is a good platform? How ‘bad’ is a bad one?
- What is the relationship between the number of apps and the level of utility? For instance, is it a linear or a concave function? What is the slope?

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[125] Differences in brand perception are also not incorporated in the model.

- Ultimately, how strong is the indirect network effect? Is an inferior platform with many apps more preferred than a superior platform with few apps?

Various direct and indirect methods are proposed in the literature to measure preference structures (cf. Vriens 1995, pp. 4-12; Helm & Steiner 2008). The most notable method is conjoint analysis, which has gained widespread adoption both in research and in practice since the 1970s and is widely applied for new product development. In the context of this study, the method is used for the empirical calibration of the users' preference structures.

Conjoint analysis is a decompositional method to understand consumers' choices among multi-attribute products or services.[126] Closely related to experimentation, respondents provide preference ratings for a number of hypothetical products, termed 'stimuli', which have been designed by the researcher. Based on a statistical analysis of the responses, conjoint analysis allows the researcher to 'decompose' the *overall* evaluation to quantify the effects of *individual* attributes on aggregate utility and consumer choice.[127] The underlying assumption is a compensatory decision-making process where a negative evaluation of one attribute can be compensated for by positive evaluations of others.

7.4.2.1 Design of the conjoint analysis

The design of a conjoint analysis involves the choice of a conjoint methodology, the design of the stimuli (factors and factor levels), as well as decisions regarding the presentation method and preference measure. All steps are briefly described below.

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126 A detailed description and review of the methodology would go beyond the scope of this chapter on model calibration. For a good introduction to conjoint analysis please refer to Orme (2010), Bakken & Frazier (2006), Hair et al. (2010, pp. 261-334) and Vriens (1995). Gustafsson et al. (2001) cover recent developments and related topics. Garcia et al. (2007) demonstrates how conjoint part-worths can be used to calibrate agent-based simulation models. Similar to my research focus, Gupta et al. (1999) also apply a conjoint approach for investigating indirect network effects.

127 In this regard, conjoint analysis is similar to the analysis of variance (ANOVA) for experimental data. In both cases, a limited number of (non-metric) independent variables are systematically varied to evaluate their impact on a (metric) dependent variable (Hair et al. 2010).

I apply the traditional conjoint analysis instead of the adaptive or choice-based approach.[128] Corresponding to the platforms' inherent value and network value in the model, the respondents were asked to evaluate a number of hypothetical smartphones distinguished by two attributes, or 'factors': (1) the *quality* of the operating system, and (2) the number of available *apps* for the smartphone. The number of factors and factor levels are critical in a conjoint analysis.[129] Increasing the number of factors and factor levels better reflects the differences between the stimuli and enhances the reliability of the results. However, it also drastically increases the required minimum number of stimuli and task complexity for the respondents. In order to balance these considerations, a 3x5 design is chosen with three factor levels for the *quality* attribute and five factor levels for the *apps* attribute (see Table 7-4).

Table 7-4 Factors and factor levels of the stimuli

Factor	*Factor levels*
Quality	▪ Low ▪ Average ▪ High
Apps	▪ No apps available ▪ 2,500 apps available ▪ 5,000 apps available ▪ 10,000 apps available ▪ 50,000 apps available

A sufficiently large number of factor levels for the *apps* attribute is required to reliably determine the relationship between the number of apps and the level of utility based on the respondents' evaluations. The quality of the hypothetical smartphones is evaluated with an abstract "superattribute" (Hair et al. 2010, p. 283) instead of a set of more detailed sub-attributes. In order to provide communicable and actionable measures, examples are given for both attributes to

128 There are several reasons for the traditional conjoint methodology: (1) a small number of factors, (2) a high-involvement decision, (3) the focus on the preference structure, (4) the unlikeliness of interaction effects, and (5) the desire to reduce task complexity (Hair et al. 2010, p. 313).

129 In particular, inter-attribute correlations, prohibited pairs and adverse level effects have to be considered (Hair et al. 2010, p. 279-283).

help less technically adept respondents to better understand the implications, in particular for the *quality* attribute. Furthermore, two pretests ensured the effectiveness of the conjoint task.

It is assumed that interaction effects between the two factors are nigligible. Accordingly, an additive composition rule for the conjoint analysis is used so that the aggregate utility of a stimulus is the sum of its part-worths. This also corresponds to the type of utility function used in the simulation model. Regarding the selection of the part-worths relationship, a linear model is supposed for the *quality* factor.[130] For the *apps* attribute, separate part-worth estimates are used because the intervals are not consistent among levels. Furthermore, it is the most general form with the highest degree of flexibility.

The stimuli are presented containing both attributes using the full-profile method, which is recommended for six or fewer factors (Hair et al. 2010, p. 287).[131] Given that the two factors have three and five factors levels each, the number of stimuli cannot be reduced by a fractional factorial design that is both orthogonal and balanced. Hence, I use a full-factorial design with all 15 stimuli to be evaluated by each respondent.[132]

The conjoint analysis applies a rating preference measure instead of a rank-order method, which is problematical to administer with 15 stimuli. Respondents were requested to evaluate the stimuli by stating their (hypothetical) willingness-to-pay for each profile.[133] In this study, the willingness-to-pay is purely used as a proxy for the perceived benefit or utility of a stimulus.[134] The chosen "dollar-metrics" approach (Orme 2010, p. 158) has the benefit of

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130 I also estimated the model using separate part-worth estimates for the *quality* attribute. The results showed that the relationship is in fact approximately linear.

131 Alternatively, the older trade-off approach or the pairwise comparison method could be applied. However, the chosen full-profile method is regarded as the most realistic form of presentation.

132 Green & Srinivasan (1978, p. 109) recommend a maximum of 30 stimuli in order to "maintain the respondent's interest in the task". Thus, 15 stimuli can be reasonably used in a conjoint analysis without a loss of data quality.

133 Respondents were explicitly asked to disregard their personal financial situation for the evaluation task. Furthermore, the instructions included an anchor value, stating that smartphones are currently priced between 150 and 650 EUR.

134 As such, the reported willingness-to-pay should be treated with some caution. A more realistic conjoint analysis to examine actual pricing decisions of smartphones would need to take many other product attributes into account. Here, the simplified approach solely serves to calibrate

providing a ratio scale measurement. Furthermore, respondents evaluate the stimuli in a realistic fashion without the need for predefined, ‘artificial’ response categories of rating scales. For instance, respondents were asked “How much would you be prepared to pay for a smartphone with an operating system of high quality and 5,000 applications available? [in Euros]?” Appendix A provides screenshots of the computer-based conjoint task, including the instructions for the respondents and presentation of the stimuli.

7.4.2.2 Results of the conjoint analysis

To analyze the results, I first focus on the disaggregate level before assessing the overall fit of the model and moving to the interpretation of the average part-worths.

N=199 respondents participated in the conjoint analysis.[135] The traditional regression-based approach is employed to derive part-worths estimates. To begin with, estimation is performed for each respondent separately. Based on these initial results, cases with (1) missing ratings for some stimuli, (2) out-of-range values, or (3) illogical patterns in the part-worths are excluded from further analysis. It can be reasonably assumed that, ceteris paribus, consumers prefer high quality over low quality, and more apps over few apps. As recommended by Hair et al. (2010, p. 300), cases that violate these monotonic relationships, termed ‘reversals’, are removed.[136] After data cleaning, N=157 cases remain for further analysis. In order to assess the overall goodness-of-fit of the estimated model, the Pearson correlation r is calculated to compare actual values with predicted values. Furthermore, the respondents’ ratings are converted to rank orders and Kendall’s tau τ is determined. Both measures ($r = .993, p < .000$; $\tau = .962, p < .000$) indicate a very good fit of the model. Moving to the interpretation of the results, Table 7-5 shows the model estimation at the aggregate level to portray the average evaluation of the N=157 respondents.

consumers’ utility function in the model and is believed sufficient for the evaluation of platform quality vs. apps.

135 This fulfills the recommended sample size of about 200 respondents (Hair et al. 2010, p. 292) to provide acceptable margins of errors.

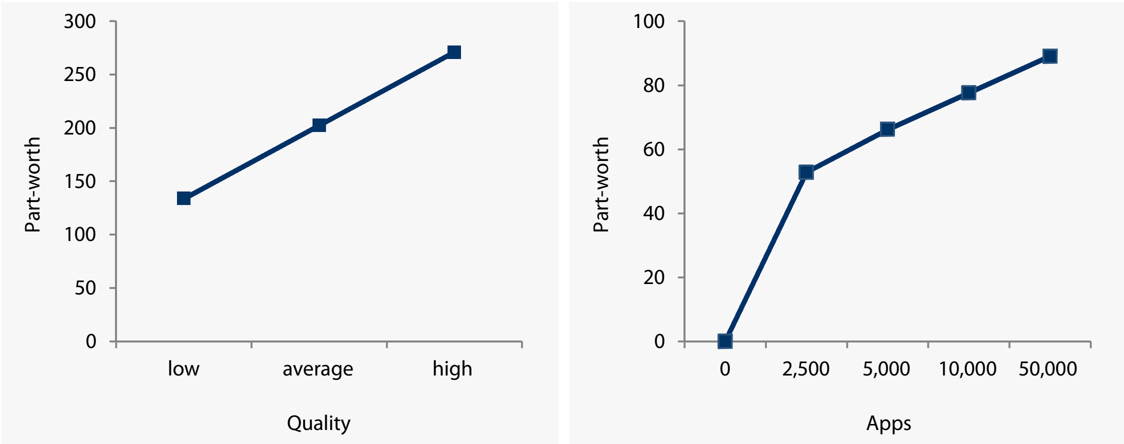
136 Reversals are a common situation in conjoint analysis. Please refer to Hair et al. (2010, pp. 300-302) for a detailed discussion of the topic.

Table 7-5 **Results of the conjoint analysis: average part-worth estimates**

		Model estimation		
Factor	*Factor level*	*Part-worths*	*Std. error*	*Rescaled part-worths*
Quality	▪ Low	-68.607	3.116	133.854
	▪ Average	0.000	0.000	202.461
	▪ High	68.607	3.116	271.068
Apps	▪ No apps available	-57.148	5.089	0.000
	▪ 2,500 apps available	-4.329	5.089	52.819
	▪ 5,000 apps available	9.096	5.089	66.244
	▪ 10,000 apps available	20.478	5.089	77.626
	▪ 50,000 apps available	31.903	5.089	89.051
(Constant)		259.609	2.545	-

I focus on the rescaled part-worths in the right column to simplify interpretation. In the absence of complementary apps, the average willingness-to-pay for a smartphone with an operating system of low quality is 134 EUR. For stimuli of average and high quality, respondents show an average willingness-to-pay of 202 EUR and 271 EUR, respectively. Focusing on the *apps* attribute, the average willingness-to-pay increases by 53 EUR when there are 2,500 compatible apps available. In the case where the consumers have 50,000 apps to choose from, the average willingness-to-pay increases by 89 EUR as opposed to the 'no apps' stimuli. The results show that the marginal willingness-to-pay diminishes with larger numbers of apps. For instance, an increase from 0 to 5,000 apps is worth 66 EUR, whereas an increase from 5,000 to 10,000 apps is valued at 11 EUR. This concave relationship can be seen on the right hand side in Figure 7-9, which depicts the rescaled average part-worths for all factor levels.

Figure 7-9 **Part-worth estimates for aggregate results**



To assess the relative importance of quality and apps, I calculate average importance values for both attributes.[137] *Quality* has the greatest contribution to overall willingness-to-pay with an importance value of 61.8 percent, as opposed to the *apps* attribute with an importance value of 38.2 percent.

7.4.2.3 Estimation of the utility function for apps

The conjoint analysis has provided average part-worth estimates for a number of hypothetical stimuli. For instance, we know how much consumers value 2,500, 5,000, 10,000 and 50,000 available apps for a smartphone platform. For the simulation model, however, this empirical evidence needs to be translated into a continuous utility function that represents users' benefit for any arbitrary number of apps. For that purpose, I estimate the utility function by performing nonlinear regression on the part-worth estimates from the conjoint analysis. Inspection of the part-worths for the *apps* attribute (Figure 7-9) reveal that the marginal benefit decreases with larger numbers of apps. As such, an asymptotic regression model seems appropriate. I employ the modified exponential function already introduced in the model description (section 5.3.3.2):

$$Util^{\mathrm{nwk}}(g, \alpha, \beta) = \alpha\left(1 - e^{-\frac{\beta}{1000}g}\right), \qquad \alpha, \beta, g \geq 0.$$

137 The importance value is defined as the part-worth range for each factor divided by the total range (Orme 2010, p. 79).

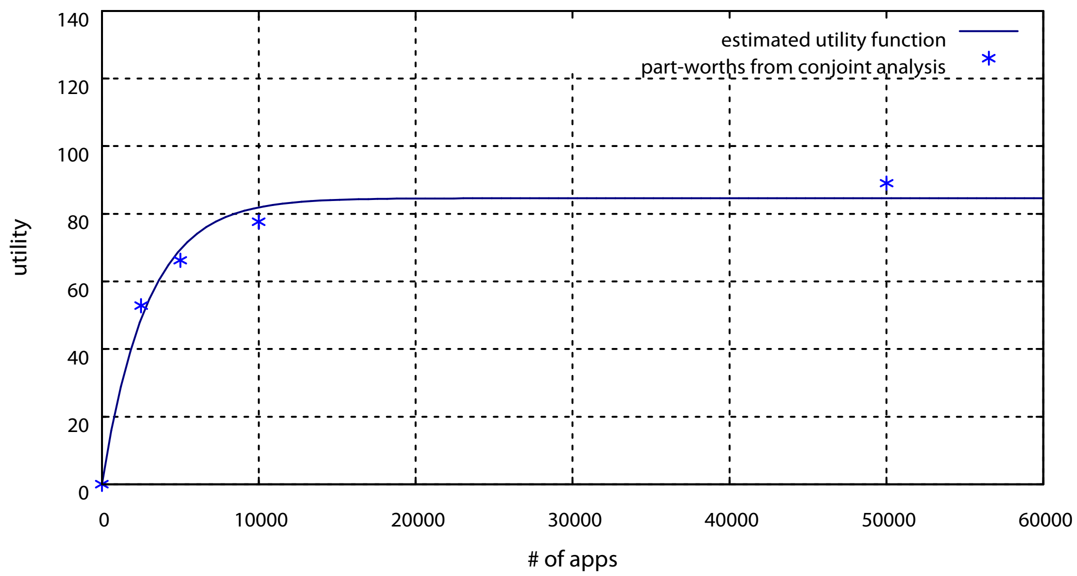
The network value, i.e., the benefit from the availability of complementary products, is a function of the number of apps g and two parameters α, β that describe the utility function. The nonlinear regression procedure in SPSS requires starting values for the parameters. For the upper asymptote a starting value of $\alpha = 90$ is chosen, which is slightly above the maximum part-worth. For the gradient parameter, the slope between two distant points determines the starting value = 0.2 . Table 7-6 shows the resulting parameter estimates from the nonlinear regression analysis.

Table 7-6 Results of the nonlinear regression: estimated parameters of the utility function

			95 % confidence interval	
Parameter	*Estimate*	*Std. error*	*Lower bound*	*Upper bound*
α	84.600	3.675	72.903	96.296
β	.344	.052	.177	.511

For the upper asymptote, the standard error and the confidence interval are relatively small with respect to the estimated value of $\alpha = 84.6$. For the gradient parameter β, there is a greater degree of uncertainty. R-squared is calculated with reference to the residual sum of squares and the corrected total. $R^2 = .987$ shows that the model has a good fit, as can be seen in Figure 7-10. It should be stressed, however, that a nonlinear regression analysis based on only five data points has inherent limitations.

Figure 7-10 **Estimated utility function based on conjoint part-worths and nonlinear regression**



Finally, the model parameter $U^{\text{nwkeffect}}$ is calculated based on the estimated value for a and the part-worth for an average platform quality:

$$U^{\text{nwkeffect}} = \left[\frac{\text{max network utility}}{\text{max total utility}}\right] = \frac{\alpha}{\alpha + p^{\text{avgqual}}} = \frac{84.6}{84.6 + 202.5} = 0.295$$

The gradient parameter U^{utilgrad} equals the estimated β, so $U^{\text{utilgrad}} = 0.344$.

To conclude, research on consumers' preference formation for smartphones shows that, on average, platform quality is more important than the indirect network effect resulting from the availability of apps, as expressed by the higher importance value for the *quality* attribute. As a result, the relative strength of the indirect network effect is rather low for the smartphone industry, represented by $U^{\text{nwkeffect}} = 0.295$. Furthermore, the results provide quantitative empirical evidence that consumers clearly value a larger variety of apps for their smartphones, but that the marginal benefit diminishes. When there is already an adequate portfolio of apps, a further expansion yields smaller and smaller increases in utility. In the conjoint analysis, the saturation point was around 15,000 apps, so $U^{\text{utilgrad}} = 0.344$. In summary, the results from the conjoint analysis in combination with a nonlinear regression model are employed to empirically calibrate the utility function incorporated in the simulation model.

7.4.3 Rationality level

In the simulation model, user agents act in a boundedly rational manner and cannot perfectly assess the quality of the platforms. Hence, their evaluation is biased by a quality perception variance, determined by the model parameter $U^{\text{ratiolevel}}$, which may lead to non-optimal decisions.

For the calibration of users' rationality level, I rely on data from a consumer experiment by Langer (2011). The experiment consists of repeated choices between two hypothetical smartphones A and B in a series of eight decision rounds. Smartphone B turns out to be the superior product, in terms of higher quality and lower price. I focus on experimental group number eight, which displayed low learning effects, low complementarity effects and low adaptive expectations effects (Langer 2011, p. 64). For this experimental group, smartphone B is superior to smartphone A in every aspect. Nevertheless, even after eight decision rounds about 18 percent of the participants stick to the inferior choice.[138]

Based on this empirical evidence, a simulation experiment is conducted to estimate the value for the model parameter $U^{\text{ratiolevel}}$ that closely resembles the irrational response behavior encountered in the consumer experiment. With perfect information $U^{\text{infolevel}} = 1.0$ and no network effects influencing the choices, a rationality level of $U^{\text{ratiolevel}} = 0.7$ is found to replicate the empirical fraction of approximately 18 percent 'irrational' decisions. Although the simulation model behavior and the evidence from the consumer experiment cannot be directly compared, it is believed that this attempt to provide some form of empirical calibration gives a rough approximation of the level of irrationality in consumers' decision-making. Special attention will be given to the rationality level parameter in the simulation experiments to better understand the impact of the empirically calibrated value.

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138 Alternatively, one could employ the number of reversals in the conjoint experiment to measure the level of irrational behavior. Ceteris paribus, consumers should prefer high quality over low quality, and more apps over few apps. The conjoint analysis reveals N=30 cases that violate these monotonic relationships, termed 'reversals'. In relation to the overall sample size of N=199, reversals thus account for 15 percent. Interestingly, the fraction of 'irrational' responses is comparable to the 18 percent of participants in the consumer experiment who choose a clearly inferior product.

7.4.4 Switching behavior

The simulation model assumes that users are able to switch platforms. However, they are bound to their platform choice for a certain decision-horizon period U^{horizon} before they can reconsider their platform choice. For the smartphone industry, this decision horizon corresponds to the length of ownership before consumers replace their device and decide on a new smartphone.

A recent study by J.D. Power (2010) reports that consumers keep their mobile phones for an average of 20.5 months. This corresponds to the typical two-year contracts with mobile service providers, after which subscribers often have the option to upgrade to a new device. On these grounds, a decision horizon of two years is assumed, equaling 104 time steps in model time. As such, the model parameter for users' decision horizon, which is defined relative to the total model runtime of 1,300 time steps, is empirically calibrated to $U^{\text{horizon}} = 0.08$.

7.5 Complementors: evidence from semi-structured interviews with application developers

Having empirically calibrated the information search and decision-making behavior of user agents in the simulation model, I devote this subchapter to the calibration of the complementor agents. Semi-structured interviews with smartphone application developers provide insight into their objectives, decision heuristics and behavior. For that purpose, my colleague and I attended four industry conferences between autumn 2009 and summer 2010: *OSIM World 2009* (15-16 Sept. 2009, Amsterdam), *Droidcon 2009* (03-04 Nov. 2009, Berlin), *Droidcon 2010* (26-27 May 2010, Berlin) and *WIPJam@IT Profits* (09 June 2010, Berlin).[139]

At these conferences, I evaluated the key notes and presentations, took the role of a "participant as observer" (Jarzabkowski 2010) in discussion rounds and interviewed application developers and other industry experts. To capture the data, I tape-recorded the sessions where possible and/or took notes during and afterwards. Consistent with the iterative nature of simulation research, the development of the simulation model took place simultaneously with this empirical field work. Once the model had reached an advanced stage, I developed a guideline for conducting semi-structured interviews with application developers. This semi-structured approach helped to focus on information that is required to calibrate the model parameters, but also provided enough degrees of freedom in the conversation. The interview guideline can be found in 0. I guaranteed confidentiality to all interviewees and participants in discussion groups. Hence, their names and company affiliations are not disclosed. All German quotations were translated into English by the author.

Overall, empirical evidence shows that the platform choice is a major topic for app developers. Questions of industry fragmentation, the future prospects of the competing smartphone platforms and solutions for multi-platform development were intensively debated at all conferences. Third-party application developers, also termed 'independent software vendors (ISV)', incur upfront costs when developing platform-specific apps for smartphones. They must decide on their platform strategy in the context of a rapidly changing competitive environment. For instance, the *Symbian* platform has gone from market leader to de-facto discontinuation in

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less than two years. As a result, developers face a high uncertainty regarding their platform strategy:

> "We don't know which platform will be the winning platform."
> (Manager of a German network operator, *Droidcon 2009*)

> "As an application developer, a part of your investment is in a very uncertain area because you don't know what the future brings."
> (Large independent software vendor, *OSIM World 2009*)

> "There is a big fight going on at the moment. As a developer, you cannot support all of the platforms."
> (Application developer, Games industry, *Droidcon 2010*)

7.5.1 Maximizing reach

For developers, the competition between smartphone platforms results in a fragmented market that is difficult to address. They develop platform-specific apps and face additional development effort when supporting multiple platforms:

> "From a developer's perspective, you have to support different platforms, which means you have a lot of additional development work."
> (App developer, *Droidcon 2010*)

> "Typical drawbacks are the effort and complexity of supporting several native platforms (or limiting your app to one platform)."
> (Mobile Developer's Guide, p. 4, Enough Software 2011)

Especially among small- and medium-sized software companies, there is consensus that not all platforms can be supported due to the additional development effort for porting an application to another platform:

> "Fragmentation is a big issue. Of course we have to support multiple platforms, but it is not possible for a developer to support all of them."
> (Independent software developer, medium-sized enterprise, *Droidcon 2010*)

> "There are different approaches to deal with the current variety of smartphone platforms in the marketplace: the most obvious way is to directly support all the different platforms. … But it is also the most expensive one and not possible for small developers."
> (Industry expert, *Droidcon 2009*)

> "You can do it [i.e., support all platforms] if you are a Fortune 500 company, but if you are a one or two-man show you have no chance."
> (App developer, *WIPJam@IT Profits 2010*)

> "We can only do [i.e., support] one or two platforms."
> (CEO, small software company, *OSIM World 2009*)

When asked about their decision criteria for platform choice, developers report a number of objectives. Foremost, the user base, or size, of a platform is critical. Developers prefer to develop for platforms with as many users as possible. Furthermore, developers appreciate easy monetization, well-documented development tools and convenient application programming interfaces (APIs), as well as a large developer community to share knowledge and best practices. They also favor smartphone platforms which allow them to build on existing experience and programming skills. One conference participant summarizes it as follows:

> "We are pragmatic: we look at the benefits of platforms, we look at the ecosystems, of course it's a skill question of what you do, the momentum that you have, and you look how you think you can make money — and based on that you choose your platform. It's very simple."
> (Product manager, *OSIM World 2009*)

Among the various objectives for developers, the interviews revealed that *maximizing reach* is the dominant decision criterion. In order to increase the potential customer base for their apps, developers focus on platforms with a large user base:

> "The most important factor is market share in terms of installed base."
> (Manager, telecom industry, *Droidcon 2010*)

> "You want to get the largest reach across platforms to be able to have the largest addressable market."
> (Project leader, large software company, *OSIM World 2009*)

> "There is a lot of fragmentation here. … If you deal with it, you can provide the best user experience to your users, you can differentiate yourself from the competition and last but not least you can also gain the broadest possible reach in your customer base."
> (App developer, *Droidcon 2009*)

A one-hour discussion group at *IT-Profits 2010* specifically addressed the decision criteria for platform choice in the smartphone industry. Asked what drives developers' decision in terms of which platform to adopt, they responded:

> Developer 1: "The decision is primarily driven by how many users and phones are out there."
>
> Developer 2: "Yes, it's reach, reach, reach! I mean it's about monetization, you have to earn money somehow. Whoever has the most reach wins."
> (App developers, *WIPJam@IT Profits 2010*)

To conclude, the empirical evidence collected suggests that the reach-maximizing decision heuristic for complementor agents in the simulation model is well suited to represent the decision behavior of application developers in the smartphone industry.

7.5.2 Synergy level

When application developers support multiple platforms, they engage in a trade-off between higher market coverage, termed *reach*, and longer development cycles:

> "You can go with a very narrow solution to get a faster time to market. … But most of the time, it is about getting a broader reach."
> (Independent software vendor, *OSIM World 2009*)

The field work showed that developers deliberately balance the additional effort for supporting a platform with the expected gain of a higher reach. Thus, their decision whether to support a certain platform depends on the market share of the respective platform and the level of synergies for multi-homing. In general, the interviewees stated that the synergies of cross-platform development strongly depend on the type of application and are difficult to quantify. For instance, porting a sophisticated 3D game to another smartphone platform requires much more effort compared to a rather simple weather forecast app that displays data received from a server. Usually, the back-end (program logic, data structure, server-based services) can be easily re-used, whereas the front-end (user interface) needs to be tailored to the platform. This user interface "can constitute over 50% of the entire codebase" (Enough Software 2011, p. 149). Furthermore, the level of synergies is influenced by the use of middleware abstraction layers and cross-compiling frameworks:

> "There are different usage paradigms for different platforms, so to say 'what the user expects', for instance toolbar vs. menu, because every app does it the same way. You need to adhere to this, otherwise it won't feel like part of the system. … You have to do additional work for every platform."
>
> (App developer, *WIPJam@IT Profits 2010*)

> "It is hard to quantify and it really depends on the type of application, but we typically re-use 25 to 60 percent of the code when porting the application to another platform."
>
> (Project leader, medium-sized software company, *OSIM World 2009*)

> "Porting our application to the Android platform was quite a task and took about two months. … Overall, I would estimate that we utilized 30 to 40 percent of the existing codebase."
>
> (App developer, *OSIM World 2009*)

To conclude, the field work revealed different assessments within the developer community about the level of cross-platform synergies. Taking a rather cautious view, the model parameter related to the development synergies when supporting multiple platforms is calibrated to $C^{\text{synlevel}} = 0.3$, which means than 30 percent of the development resources are directly beneficial for cross-platform development. Based on this synergy level and the market shares of the competing platforms, complementor agents choose the reach-maximizing strategy.

7.5.3 Switching behavior

The interviews showed that developers revise their platform strategy in the light of recent changes in platforms' market shares. For that purpose, they rely on market share estimates regularly published by various research companies, in particular *Gartner*. An interviewee described the company's switching decision as follows:

> "It's a question of how much courage we have, whether we say 'Ok, now we ignore, for example, Symbian, because it is a dying platform'. At the moment, Symbian still has a noteworthy market share. … So if we ignore Symbian, we ignore 20 percent of the market. 'Can we?' one might ask. 'Yes?' And we keep asking until it is only ten percent and then we do it, then we just ignore it [the Symbian platform], if the trend is foreseeable."
>
> (Manager, telecom industry, *Droidcon 2010*)

Most developers reported that they reassess their platform strategy only at certain times, for instance when new quarterly and yearly market share data is published, or before they engage in a large-scale development project. Furthermore, developers do not change their platform strategy very often due to platform-specific resources such as human knowledge or physical equipment, which hinder continual 'platform hopping':

> "You almost need to have an expert for each platform."
>
> (Project manager, *WIPJam@IT Profits 2010*)

> "It depends on the platform, but in general the initial learning effort is quite high when switching platforms. … You should think twice."
>
> (App developer, *OSIM World 2010*)

Although developers rely on emulators for testing and debugging of their apps, i.e., computer programs that simulate a phone device, ultimately the software needs be tested with real physical smartphones:

> "The various testing devices are a particular cost factor when supporting multiple platforms."
>
> (Developer, *OSIM 2009*)

In the model, the various forms of switching costs, friction and delays are combined into a single measure, the 'decision horizon'. Given that developers put so much emphasis on annual market share reports, it is assumed that they reassess their platform strategy every 12 months. As such, the decision horizon model parameter, which is defined relative to the total model runtime of 1,300 time steps, is calibrated to $C^{\text{horizon}} = 0.04$.

7.5.4 Number of apps over time

In the smartphone industry, the strength of the indirect network effect depends on the number of apps available for a particular smartphone platform. In this regard, the timing is important: does the indirect network effect increase *slowly* over the course of many years, or does it emerge *instantly* after the market launch of a platform? In other words, how long does it take developers to establish a large portfolio of applications that has a considerable impact on consumers' platform choices?

In order to empirically calibrate the model, the interval between the launch date of a platform and the reaching of the 50,000 apps milestone, which corresponds to the maximum number of apps in the conjoint study, is measured for the two most popular smartphone platforms: the *Apple iOS (iPhone)* and *Google Android*. In both cases, the start of general product availability marks the launch date. Statistics on the number of available apps are taken from press releases and third-party studies.[140] The first *Apple iPhone* was introduced in June 2007 and the *Apple App Store* reached 50,000 apps approximately 25 months later in July 2009. The first *Google Android* handset was launched in October 2008. About 22 months later the *Android Market* contained more than 50,000 apps. These findings indicate that it takes about 24 months for a successful platform to reach a portfolio of 50,000 apps. That said, the first two years after the product launch are critical for a platform provider to get application developers on board.

The simulation model is calibrated to match these empirical findings. The interviews revealed that the development time for an app fluctuates widely from a few man-days to hundreds of man-days, depending on the type and complexity of the application. It is assumed that each developer agent requires about three months, equivalent to 13 model time steps, to develop one application in the case of single-homing. As such, the resource intensiveness parameter is calibrated to $C^{res} = 13$.

For performance reasons, the number of complementor agents in the simulation is limited to 50 ($C = 50$),[141] as opposed to the thousands of app developers in the real world. As a consequence, the output of the 50 developer agents, in terms of apps developed, needs to be

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140 The history of the smartphone platforms is discussed in detail in Appendix A. For the number of apps available for the *Apple iPhone* and *Google Android* platforms, please refer to Figure 6-3.

141 This parameter setting will also be verified in a robustness check at a later stage (see section 8.11).

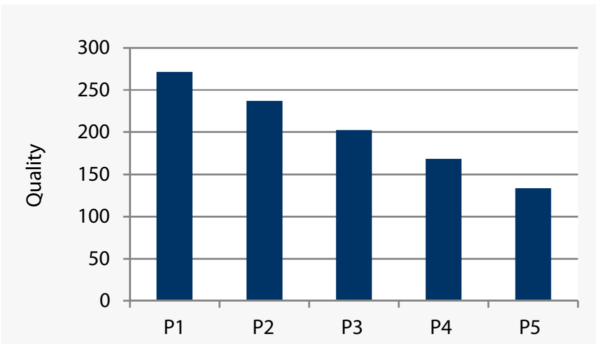
upscaled to match the empirical findings discussed above. In the simulation, the 50 developer agents gradually enter the market once a platform becomes available. Two years later, equivalent to approximately 100 model time steps, they have developed about 50,000 apps for the platform.

7.6 Platforms

A quick analysis of the competitive landscape (section 6.3) shows that there are currently five major platforms in the smartphone industry: *Apple iPhone, Google Android, Symbian, Windows Mobile* and *BlackBerry* (Gartner 2011b). Accordingly, the number of competing platforms in the model is set to five (P = 5).[142] However, it should be stressed that there is no relation between the platforms in the model and the real-world smartphone platforms. Hence, the model does not make claims as to the technical inferiority or superiority of any particular smartphone platform. Instead, results from the conjoint study are used to represent five abstract platforms, ranging from 'low' quality to 'high' quality. Therefore, the estimated conjoint part-worths of the *quality* attribute determine the quality of the worst and the best smartphone platform. Using these minimum and maximum values, the quality properties of the five competing platforms are calculated by assuming equal quality differences between them.

Figure 7-11 shows the quality of the five modeled platforms based on the estimated conjoint part-worths.

Figure 7-11 **Quality of the modeled platforms based on estimated conjoint part-worths**



[142] In addition to the empirical support for five platforms, the decision whether to multi-home (and to what extent) could not be realistically modeled with only two competing platforms.

To conclude, the model parameters $P^{avgqual}$ and $P^{qualdiff}$ can be calibrated according to the procedure laid out in section 5.3.3.1. The average quality of the platforms is set to $P^{avgqual} = 202.5$ and the quality difference parameter is set to $P^{qualdiff} = 0.678$.

7.7 Summary

This chapter has described how quantitative and qualitative empirical evidence from the smartphone industry is used to calibrate the model parameters, thereby applying the generic simulation model of path dependence in two-sided markets to a specific empirical case. Table 7-7 below lists the empirically calibrated model parameters and summarizes the chosen calibration methodology and data sources.

Table 7-7 Summary of empirical model calibration

Model parameter		*Value*	*Empirical basis*
P	*Number of platforms*	5	Five major smartphone platforms
$P^{avgqual}$	*Average quality*	202.5	Evaluation for low/high platform quality from conjoint analysis, interpolated to five platforms
$P^{qualdiff}$	*Variation in quality*	0.678	See above
D^{m}	*Network: scale-free m*	4	Minimum value of five real-world influence networks (Dover et al. 2012)
D^{ext}	*Bass model: external effect*	4×10^{-6}	Replication of the empirical diffusion trajectory estimated by Sundqvist et al. (2005)
D^{wom}	*Bass model: word of mouth*	0.025	See above
$U^{infolevel}$	*Information level*	0.37	Survey results on the size of consumers' consideration set for smartphone choice
$U^{ratiolevel}$	*Rationality level*	0.7	Irrational response behavior in a consumer experiment on smartphone choice (Langer 2011)
$U^{nwkeffect}$	*Network effect factor*	0.295	Results from a conjoint analysis in combination with a nonlinear regression model: importance of apps vs. importance of platform quality
$U^{utilgrad}$	*Utility function gradient*	0.344	See above. Saturation point of the utility function at about 15,000 apps
$U^{horizon}$	*Decision horizon*	0.08	Market study by J.D. Power (2010): length of ownership before consumers replace their smartphones (two years)

Model parameter		*Value*	*Empirical basis*
C^{res}	*Resource intensiveness*	13	Empirical evidence from interviews with developers: average development time
$C^{synlevel}$	*Synergy level*	0.3	Empirical evidence from interviews with developers: percentage of development effort that is beneficial for cross-platform development
$C^{horizon}$	*Decision horizon*	0.04	Empirical evidence from interviews: developers reassess their platform strategy on average every 12 months

Apart from the empirical calibration, the field work also helped to validate the model assumptions and agent design (micro-validation). An industry analysis, a consumer survey as well as interviews with app developers provide sound evidence for the applicability of the proposed simulation model to the smartphone industry.

On the basis of the model calibration, c*ounterfactual experiments* will now be conducted to address 'what-if' scenarios for the smartphone industry. The empirically calibrated parameters provide the reference point for the variation experiments in the following chapter, which seek to explore the causal factors for technological lock-ins.

8 Simulation

The present chapter forms the core of the thesis: it investigates the conditions for technological lock-ins in two-sided markets by means of the proposed simulation model. The chapter first describes the computational implementation of the model and its verification. Second, the design of experiments defines a systematic procedure for conducting the subsequent simulation experiments. It explains the experimental factors, the factor levels and the factorial design, as well as the response variables. Furthermore, I determine the number of repeated simulation runs that are required to obtain statistically significant results from the stochastic model. Finally, the results of the simulation experiments are presented and discussed, followed by a robustness check which ensures that the identified causal relationships are stable.

8.1 Computational implementation of the conceptual model

On the basis of the conceptual model, the first step is to transform the formal model into programming code. Based on independent reviews of different simulation toolkits for agent-based simulation research (Tesfatsion 2012; Crawford 2009; Nikolai & Madey 2009; Railsback et al. 2006), I conducted initial testing with *AnyLogic 6.4.1*, *NetLogo 4.1* and *Repast Symphony 1.2*. After careful consideration of the benefits and shortcomings of the three software packages, the simulation model was developed with *AnyLogic* in its latest version (6.5.1). This toolkit is based on the JAVA programming language, which allows for object-oriented programming. *AnyLogic* is a general purpose simulation framework (system dynamics, agent-based simulation, discrete event) and thus provides the highest degree of freedom for model development and future work. In retrospect, *AnyLogic* indeed proved to be a powerful professional tool for simulation research, capable of building a sophisticated model of platform competition in two-sided markets.

The resulting JAVA program has 10,457 lines of code, which is a common metric to measure the size and programming effort of a software project. The model documentation, also containing the source code for the agent implementations, can be found in Appendix A. The two screenshots below depict the simulation setup and the model presentation at runtime.

Figure 8-1 **Screenshot of the simulation setup**
Displayed at the top is the toolbar to control the model execution (start, pause, stop, change model execution speed); below are the controls to set the parameter values for the model environment, the technology platforms, the user and the complementor agents. The depicted interface is used for manual execution of the model. The setup screen for the automated variation experiments is not shown here.

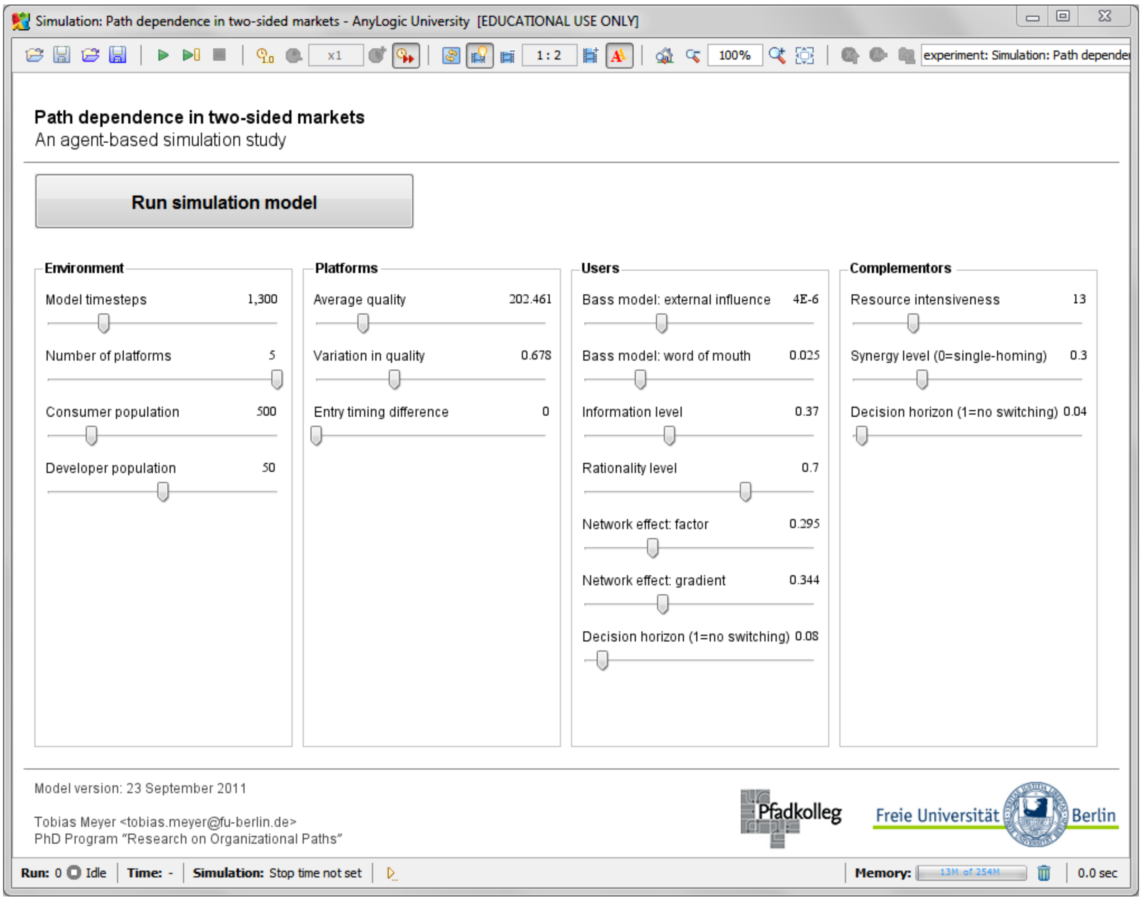


Figure 8-2 **Screenshot of the simulation at runtime**
From top to bottom: (1) users section with the innovation diffusion curve and the scale-free social network of agents; (2) complementors section with aggregated statistics on complementors' market entry timing, platform support, platform support over time and strategy over time; (3) platforms section with platform statistics as well as information on market shares and installed base over time.

In a second step, the computational model was verified by pursuing three distinct approaches (Gilbert & Troitzsch 2005; North & Macal 2007):

1) micro-level debugging using extensive logging statements to follow the life cycles of individual agents, tracing their decision logics and internal states;
2) macro-level debugging with a set of extreme test cases, where the model outcomes are easily predictable;
3) a structured code walkthrough together with an experienced programmer (two 5-hour sessions) to discuss the model implementation, check the execution sequence and debug statements.

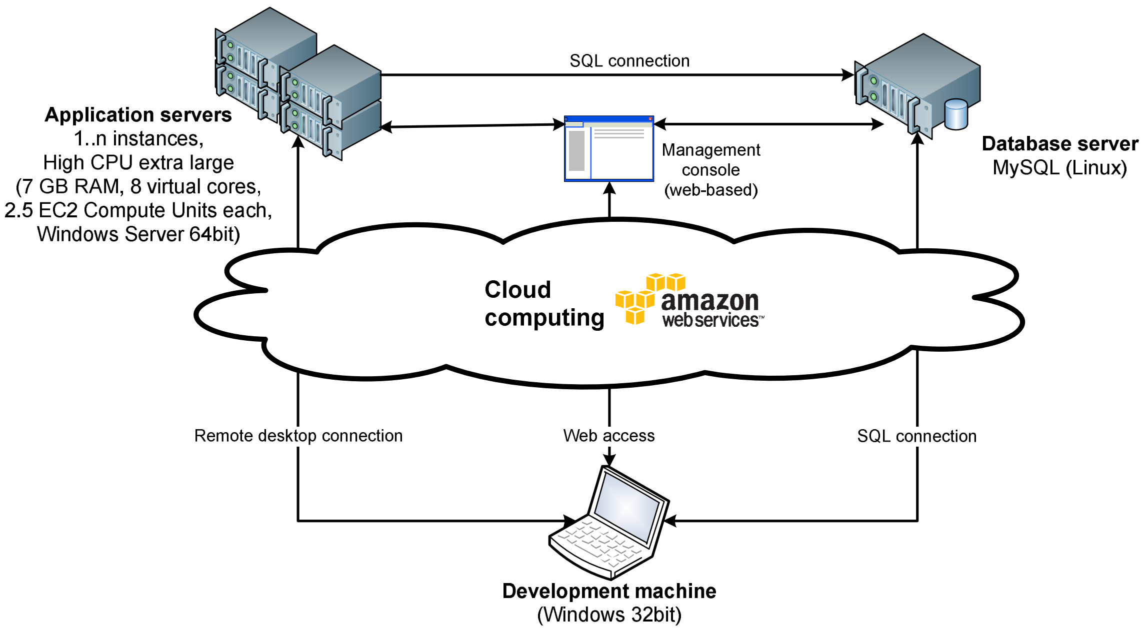
The successful verification process ensures that the computer code accurately represents the conceptual model.

As noted in section 4.3.4, the complete execution of a simulation experiment can be heavy in terms of computing time, depending on the complexity of the model as well as the number of agents involved, the number of model time steps and the number of repetitions. During the model testing phase, it became clear that limited computing power was indeed a bottleneck for the research project due to the high computing requirements of the sophisticated market model. A complete experiment, consisting of several hundred thousand runs, took more than a week to finish on a standard desktop personal computer, which made the iterative process of running and tweaking the model rather sluggish. Consequently, a more sophisticated technical setup had to be implemented. *Cloud computing* is a novel method for outsourcing IT services, such as computing tasks or data storage, to professional data centers on the internet. By combining the computing facilities of multiple powerful servers, cloud computing provides virtually unlimited computing power with a simple 'pay as you go' billing scheme. For this purpose, I employed *Amazon's Elastic Compute Cloud* (EC2), part of the *Amazon Web Services* (AWS) cloud computing platform[143], to run the experiments. Parallel execution in the cloud speeded up my simulation by a factor of 12. Furthermore, I decided to use a relational database instead of a simple file-system solution to better handle the huge amount of output data.[144] Figure 8-3 illustrates the technical setup which was used to perform the simulation runs.

143 See http://aws.amazon.com for more information.

144 All together, the simulation runs generated about 1.1 GB of output data.

Figure 8-3 **Cloud computing simulation setup**
Based on *Elastic Compute Cloud* (EC2), which is part of *Amazon Web Services* (AWS)

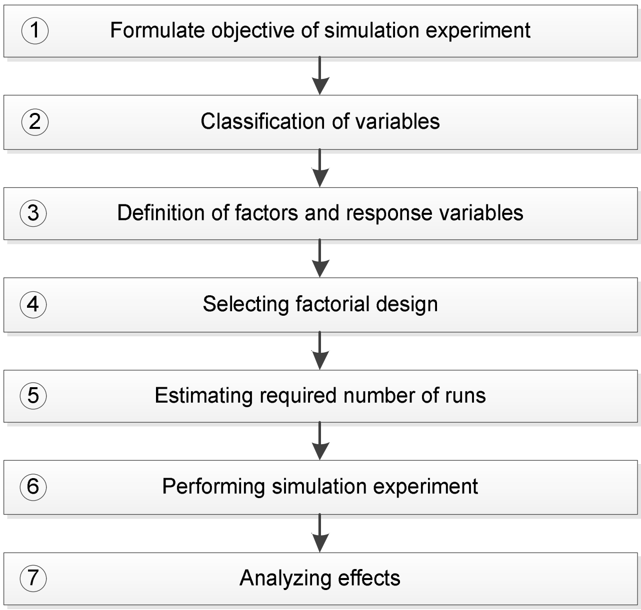


After verifying the computational model and setting up a cloud computing architecture for running the simulation, the computational model was ready for experimental usage.

8.2 Design of experiments

The analysis of the proposed simulation model is challenging due to its large number of parameters, potential interaction effects between these different parameters and possible non-linear effects (Lorscheid et al. 2012; Gilbert & Troitzsch 2005). A thorough design of experiments (DoE) is needed “so that valid and objective conclusions can be drawn effectively and efficiently” (Antony 2003, p. 7). Referring to established DoE principles for real-world experiments, Lorscheid et al. (2012) propose a systematic procedure tailored to simulation research, which is illustrated in Figure 8-4.

Figure 8-4 **The process of experimental design for simulation model analysis**
(Adapted from Lorscheid et al. 2012, p. 30)



The design of experiments for the present simulation study follows this systematic procedure. The objective of the simulation experiments is to identify the conditions that favor, or hinder, the dominance of inferior technology platforms in two-sided markets. In other words, the aim is to explore which of the model parameters have a significant effect on the probability of technological lock-ins.[145]

8.2.1 Classification of variables

As derived in chapter 3.2, this dissertation focuses on (1) the relative strength of indirect network effects and differences in platform quality, (2) the role of imperfect information and bounded rationality, (3) the influence of switching opportunities and (4) the effect of synergies that facilitate multi-homing strategies on the part of complementors. Corresponding to these selected influencing factors, the large number of model variables, necessary to describe a realistic model of platform competition in two-sided markets, is narrowed down for experimental usage. The focal parameters described above are classified as *independent variables* which are varied

[145] In contrast, a different objective for simulation experiments could be system optimization, i.e., finding the optimal parameter setting for some performance indicator (Law 2007).

throughout the experiments, whereas the remaining variables are considered fixed aspects of the model and are treated as *control variables*. The control variables can also have an influence on the simulation results, even though their effect is "not of interest with respect to the research question" (Lorscheid et al. 2012, p. 30). Still, they need to be defined plausibly. Therefore, the control variables are fixed at the empirically calibrated values, thus enhancing the external validity of the simulation model with respect to the specific industry under review.

Table 8-1summarizes the model input parameters, which are classified either as independent (IV) or control variables (CV).

Table 8-1 Summary of model parameters and their empirical calibration

Input variable	*Symbol*	*Domain*	*Classification* *	*Empirically calibrated*	*Type*	*Value range*	*Default value*	*Source*	*Description*
Number of time steps	T	Environment	CV	X	int	100..3,000	1,300		Model time, equals ~25 years
Number of runs	R	Environment	CV		int	1..5,000	1,500		Repetitions per setting
Number of platforms	P	Environment	CV	X	int	2..5	5	Gartner (2012)	5 major smartphone platforms
Number of users	U	Environment	CV		int	30..2,500	500		
Number of complementors	C	Environment	CV		int	0..100	50		
Network: scale-free M	D^{m}	Diffusion	CV	X	int	1..10	4	Dover et al. (2012)	Barabási-Albert (BA) model parameter: minimal degree
Bass model: external effect	D^{ext}	Diffusion	CV	X	double	0..1 x 10^{-5}	4 x 10^{-6}	Sundqvist et al. (2005)	+ ABS calibration experiment
Bass model: word-of-mouth	D^{wom}	Diffusion	CV	X	double	0..0.1	0.025	Sundqvist et al. (2005)	+ ABS calibration experiment
Information level	$U^{infolevel}$	Users	IV	X	double	0..1	0.37	Survey	Size of consideration set
Rationality level	$U^{ratiolevel}$	Users	IV	X	double	0..1	0.7	Langer (2011)	Quality perception variance
Network effect factor	$U^{nwkeffect}$	Users	IV	X	double	0..0.999	0.295	Conjoint analysis	Relative size of network effect
Utility function: gradient	$U^{utilgrad}$	Users	CV	X	double	0..1	0.344	Conjoint analysis	Gradient of the utility function
Decision horizon	$U^{horizon}$	Users	IV	X	double	0..1	0.08	3rd party study	Ease of switching
Resource intensiveness	C^{res}	Complementors	CV	X	double	0..50	13	Interviews	Resources needed for one complementary product
Synergy level	$C^{synlevel}$	Complementors	IV	X	double	0..1	0.3	Interviews	Ease of multi-homing
Decision horizon	$C^{horizon}$	Complementors	IV	X	double	0..1	0.04	Interviews	Ease of switching
Average quality	$P^{avgqual}$	Platforms	CV	X	double	0..1000	202.5	Conjoint analysis	Average platform quality
Variation in quality	$P^{qualdiff}$	Platforms	IV	X	double	0..2	0.678	Conjoint analysis	Quality difference between the worst and the best platform
Entry timing difference	$P^{timediff}$	Platforms	IV		double	0..1	0		Timing difference between the first and the last market entry

* Independent variables are denoted by IV, control variables are denoted by CV.

8.2.2 Factors, factor levels and factorial design

Following the terminology set out for the experimental design, the independent variables are termed *factors* and their values are referred to as *factor levels*. The resulting factor level combinations are called *design points* (Kleijnen 2008). The eight independent variables, denoted by 'IV' in the table above, translate to a total of eight factors. Regarding the factor levels, many simulation experiments only compare the effect of two factor levels (high vs. low), which is referred to as a 2^k design (Law 2007). However, it is believed that for the present research question a larger number of factor levels is required to analyze the factors' impact in greater detail. For instance, instead of only comparing the influence of weak vs. strong network effects, the study aims to explore their gradual effect on the model behavior, as well as to identify U-shaped relationships or saturation points. However, one needs to balance the number of factor levels and the 'cost' in terms of computing time for additional simulation runs. Most of the factors have a possible value range between zero and one. In this context, six factor levels {0.0; 0.2; 0.4; 0.6; 0.8; 1.0} are regarded as an adequate trade-off to analyze the factors' influence in sufficient detail.

Searching the solution space that is defined by eight factors with six factor levels each is a difficult task. With a full factorial design and only 500 repeated simulation runs for each design point, the experiment would comprise about 840 million runs (500×6^8), requiring more than 13 years (!) of computing time, thus far exceeding any reasonable limit for working with the model. Therefore, I decided to split the experiment into several sub-experiments with two factors each. The benefits of this approach are twofold: first, the model becomes more manageable in terms of computational requirements; second, the causal relationships are much easier to visualize and interpret.[146] However, the disadvantage is that potential interaction effects between factors of different sub-experiments may remain undetected.

Corresponding to the four potential determinants of lock-in put forward in chapter 3.2, the eight factors are split into four experiments, each focusing on a different aspect of the model. In each experiment, the focal factors are systematically varied while all other model parameters are fixed at their empirically calibrated values. A fifth experiment explores the influence of

[146] This view is also supported by Field & Hole (2003, p. 86), who suggest that experiments should not include more than three factors.

indirect network effects and quality differences in the special case of successive market entry. These five parameter variation experiments are preceded by a base case experiment, which is used to explore the model behavior for a range of well-known scenarios. By referring to existing theory, the aim is to relate the present simulation model to other models of path dependence and compare the results. In addition, a full calibration experiment is conducted that serves as the reference case for the parameter variation experiments. In this setting, all parameter values are fixed at their empirically calibrated values. Table 8-2 summarizes the sequence and scope of the performed simulation experiments.

Table 8-2 Sequence of simulation experiments

Experiment	*Focus*	*Factors*	
Base case	Model behavior under the assumptions of Arthur's model (1989)		
Full calibration	(reference case for the following experiments)		
Experiment 1	Relative strength of network effect, differences in platform quality	Network effect factor Variation in quality	$U^{\text{nwkeffect}}$ P^{qualdiff}
Experiment 2	Imperfect information, bounded rationality	Information level Rationality level	$U^{\text{infolevel}}$ $U^{\text{ratiolevel}}$
Experiment 3	Switching	Decision horizon (users) Decision horizon (complementors)	U^{horizon} C^{horizon}
Experiment 4	Ease of multi-homing, relative strength of network effect	Synergy level Network effect factor	C^{synlevel} $U^{\text{nwkeffect}}$
Full calibration	(in the case of successive market entry)		
Experiment 5	Relative strength of network effect, differences in platform quality (in the case of successive market entry)	Network effect factor Variation in quality	$U^{\text{nwkeffect}}$ P^{qualdiff}

For each of the variation experiments, a full factorial design is selected in which every level of every factor is paired with every level of every other factor. Although the application of a fractional factorial design could further reduce the required computing time, it is believed that the potential gains are too small and therefore do not justify the greater effort for the experimental design, computational implementation and data analysis.

8.2.3 Response variable

The present section describes the response variable, discusses its possible states and explains the operationalization. In the DoE context, the dependent variables which are used to evaluate the model behavior are termed *response variables*. In the context of the research question, the response variable is the state of the market at the end of the simulation when $t = T$. The variable has a nominal scale of measurement and can indicate either an oligopoly state (OLI), a first-degree lock-in (LCK1), a second-degree lock-in (LCK2) or a third-degree lock-in (LCK3).

The different degrees of lock-in draw upon efficiency considerations proposed by Liebowitz & Margolis (1995), which have been discussed in detail in section 2.1.4. If none of the technology platform ultimately achieves a dominant market position and several platforms coexist with noticeable market shares, the market state is called an oligopoly (OLI). A first-degree lock-in is defined as the persistent market dominance of a single technology platform that is not inferior to other possible alternatives, i.e., either the optimal outcome has been achieved or all outcomes are equally efficient. A second-degree lock-in denotes the persistent market dominance of a single platform which is suboptimal *in retrospect*. This state refers to an incumbent platform that defends its market leadership against new entrants with superior quality. Lastly, a third-degree lock-in is defined as the persistent market dominance of an inferior platform, although a better outcome could have been achieved, i.e., "there exists or existed some feasible arrangement for recognizing and achieving a preferred outcome, but that outcome is not obtained" (Liebowitz & Margolis 1995, p. 207). In other words, a third-degree lock-in is remediable and thus clearly inefficient. Table 8-3 summarizes the four possible states of the nominal dependent variable and their three distinguishing criteria.

Table 8-3 Response variable: specification of market states

		Criteria		
		(1) Persistent dominance	*(2) Suboptimality*	*(3) Remediability*
		Persistent market dominance of a platform	Dominant platform is inferior to another	Optimal solution could have been achieved
State				
OLI	oligopoly of technology platforms	-	-	-
LCK1	1st degree lock-in	✓	-	-
LCK2	2nd degree lock-in	✓	✓	-
LCK3	3rd degree lock-in	✓	✓	✓

How are the three criteria operationalized in the simulation model? Regarding the first criterion of persistent dominance, various measurements are used in the literature to evaluate market power, most notably (1) the Lerner index, (2) the Herfindahl-Hirschman index (HHI) of market concentration and (3) the market shares of the n largest firms I_n (Melnik et al. 2008).[147] After evaluating all options, I decided to implement a rather simple but effective measure based on the market share of the single largest firm. A platform is considered dominant if it has a market share above 75 percent. This threshold is based on two considerations. First, according to the European Court of Justice, a market share above 50 percent is "evidence of the existence of a

147 The Lerner index assesses market power by comparing price and marginal cost. Hence, it is not suitable for the present model, which abstracts from pricing issues. Melnik et al. (2008) demonstrate the limitations of the Herfindahl-Hirschman concentration index and propose a novel measure to assess market dominance at the firm level. They classify an individual firm as dominant when its market share exceeds a dominance threshold s^D that accounts for the market power of the next largest firm and an exogenous policy parameter γ that captures the significance of potential competition. I agree that their dominance measure is a valuable contribution for merger control and competition policy. However, for the purpose of the present study it proved to be unsuitable. Due to the mathematical properties of Melnik et al.'s measure, a market share above 50 percent would always be classified as market dominance. In light of the existing empirical examples for technological path dependence, it is believed that this threshold is not high enough to define a 'lock-in'.

dominant position" (European Court 1991, Case C-62/86), however this seems a rather low threshold to declare a technological lock-in. Second, referring to the literature on technological path dependence, *Microsoft's* market dominance, with its 90 percent market share in the PC industry, is widely referred to as a lock-in (Shapiro & Varian 1999). In light of these considerations, an average threshold of 75 percent appears suitable to classify a technology platform as dominant.

The persistence criterion is of special interest from a theoretical perspective on path dependence. Path dependence claims that 'history matters in the long run'. But how long is the long run? In the simulation, the 'long run' is limited by the fixed model time. Still, questions of time remain: a situation where an inferior platform dominates the market for only a short period of time before it is succeeded by another platform would intuitively *not* be classified as a lock-in. In contrast, the QWERTY case is widely interpreted as a technological lock-in, although the inferior keyboard standard will, sooner or later, be displaced by voice recognition or some other technological interface between the human and the computer. This brings up the following question: how long does a lock-in need to persist in order to constitute a lock-in? For the purpose of this study, I operationalize *persistence* as the time period after which it is highly unlikely that a dominant platform loses its market leadership in the absence of an external shock. A calibration experiment was used to set the persistence criterion. Based on the results of the experiment, persistent dominance is observed when a platform holds the dominant market position for at least 100 model time steps, equivalent to about two years in real time. Given this persistence criterion, out of 192,391 runs there were only 529 cases (0.3 %) where another platform was able to break a third-degree degree lock-in, as opposed to 191,862 cases (99.7 %) where a third-degree degree lock-in was identified correctly. This confidence level is sufficient to rule out type I errors, or 'false positives'.

The implementation of the suboptimality and remediability criteria is straightforward. Suboptimality relates to the quality of the platforms. A market outcome is *suboptimal*[148] if the dominant platform is inferior to at least one of the other platforms in terms of platform quality. Remediability relates to the temporal order of market entry. A market outcome is *remediable* if a

148 The criterion is deliberately termed *suboptimality* instead of *inefficiency* in order to better distinguish between second- and third-degree lock-ins. In fact, Williamson (1993) argues that an allocation is only inefficient in a strict sense if it is remediable.

dominant inferior platform entered the market after or simultaneously with a superior platform. Hence, the optimal solution could have been achieved and the allocation is inefficient *ex-ante* (Liebowitz & Margolis 1995).

To summarize, based on the criteria of (1) persistent dominance, (2) suboptimality and (3) remediability, the final state of the market is classified either as an oligopoly (OLI), a first-degree lock-in (LCK1), a suboptimal second-degree lock-in (LCK2), or an inefficient third-degree lock-in (LCK3).

8.2.4 Required number of runs

Contingency is a central element of path dependence theory. Accordingly, the simulation model incorporates elements of randomness which lead to non-deterministic simulation results. Running the model multiple times with the *same* parameter settings will produce *different* market states at the end of the simulation. In other words, even if the initial conditions are known ex-ante, the outcome of a path-dependent process is unpredictable. Hence, a single run is not sufficient to examine the model behavior (Gilbert & Troitzsch 2005). Instead, the distribution of the response variable over a number of simulation runs has to be evaluated to achieve conclusive results. Lorscheid et al. (2012, pp. 33ff.) propose an iterative process to determine the required number of repetitions based on the coefficient of variance for the response variable(s). However, their approach is not applicable to variables with a nominal scale of measurement, as is the case in the present study. A different method is needed.

As discussed, the response variable has four discrete categories which indicate either an oligopoly state (OLI), or a first-, second- or third-degree lock-in (LCK1, LCK2, LCK3). Repeated runs of the stochastic simulation model can produce different market outcomes. Therefore, the 'true' model behavior for any given set of input values is described by the frequency distribution of the four categories over a theoretically infinite number of runs.[149] In practice, this is impossible. Given finite computing resources, one can only draw a sample, consisting of a limited number of simulation runs, from the 'population' of infinite repeated runs.

149 In other terms, the result is a multinomial distribution where each of the four possible outcomes is binomially distributed.

For a parameter variation experiment, the sample size needs to be large enough to distinguish between structural effects from the variation of model parameters and random nuisance factors of the stochastic model. For instance, it needs to be ensured that a change in the relative frequency of LCK3 outcomes can be clearly attributed to a change in one of the model parameters, instead of being caused by random influences that give rise to sample-to-sample variation.

Given the binomial distribution of the discrete response categories, a simple formula can be used to determine the number of repeated simulation runs that is sufficient to estimate the 'true' model behavior with a predefined accuracy. According to the de Moivre–Laplace theorem, which is a special case of the central limit theorem, the binomial distribution can be approximated by the normal distribution given a large number of independent trials. Adapted from Cochran (1963, p. 75; see also Wild & Seber 1999), the number of repeated simulation runs R required to estimate the 'true' proportion of outcomes is denoted by

$$R \geq \left(\frac{z}{m}\right)^2 \times p\,(1-p)$$

where

z	:	the z-score corresponding to the desired confidence level,
m	:	the margin of error,
p	:	the relative frequency in the population, i.e., the 'true' proportion over an infinite number of repeated simulation runs.

For the unknown 'true' proportion in the population, the most conservative value that yields the maximum variance (p = 0.5) is chosen. Given a 95 percent confidence interval (z = 1.96) and an error margin of 3 percentage points (m = 0.03), the required number of repetitions is $R \geq 1067$. In other words, running the stochastic simulation model at least 1,067 times ensures that the determined relative frequency of certain outcomes will be ± 3 percentage points around the 'true' model behavior given a 95 percent confidence interval. As a precaution to further increase accuracy, I set the number of repetitions to 1,500, which has been found to produce acceptable margins of error in most research settings (Jaccard & Becker 2002, p. 192).[150]

By means of different parameter variation experiments, I can now explore the impact of the experimental factors on the response variable, which represents the final state of the market. The repeated simulation runs under varied conditions allow us to analyze which factors affect the frequency distribution of oligopolies, or first-, second- or third-degree lock-ins in the modeled market. The relative frequency of a certain event in a large number of trials can also be interpreted as the *probability* of that event, following the frequentist school of John Venn and others.[151] In the long run, the relative frequency converges to the probability of an event:

$$\text{Prob}(x) = \lim_{R\to\infty}\left(\frac{n_x}{R}\right)$$

where

R	:	the total number of trials, i.e., the repeated runs in the simulation context,
n_x	:	the total number of trials where the event x occurred, i.e., the number of simulation runs with the final market state x.

As only finite sequences can be observed, a simplified version of frequentism holds that "the probability of an attribute A in a finite reference class B is the relative frequency of actual occurrences of A within B" (Hájek 2010) given a large number of trials. For instance, by counting the simulation runs that lead to a third-degree lock-in as a proportion of the total number of runs, the relative frequency can be interpreted as the probability for a third-degree lock-in given a set of initial conditions. Consequently, varying the model parameters allows us to identify the factors that increase or decrease the probability for technological lock-ins.

This excursus on the importance of repeated runs, the relative frequency of different model outcomes and the probability of lock-in sets the scene for a thorough understanding and interpretation of the simulation experiments, which are presented in the following sections. The

150 This further reduces the margin of error to ± 2.5 percentage points for $p = 0.5$. For more skewed distributions, the margin of error is even smaller (e.g., ± 1.5 percentage points for $p = 0.1$ / 0.9 and $R = 1500$).

151 Please refer to Hájek (2010) for an overview of the various concepts of probability, where objective as well as subjective (Bayesian) interpretations are explained in detail.

aggregate results of the experiments are analyzed by means of graphical representation of the effect sizes. The large and statistically-robust number of simulation run repetitions ensures that changes in the dependent variable above the margin of error are caused by variations in the independent variables. Therefore, statistical tests on the direction and significance of the effects would not yield additional insights and are thus omitted.

8.3 Base case experiment: A perfect world

The base case experiment is used to explore the model behavior for a range of hypothetical, extreme scenarios. By referring to existing theory, the aim is to relate the present simulation model to other models of technological path dependence and compare the results. Thus, the overall objective of the base case is to build trust in the model and to strengthen its internal validity (Davis et al. 2007).

The experiment setup follows the assumptions of the seminal model of competing technologies by Arthur (1989). The model behavior is explored under constant and increasing returns, i.e., in the absence and presence of indirect network effects. In addition to Arthur's model, the simulation model is run with and without differences in platform quality. In line with Arthur's model, agents have complete information on all competing technologies and act in a perfectly rational manner. Hence, the base case scenario represents the ideal (neoclassical) world with perfect information and fully rational actors. Furthermore, neither users nor complementors can revise their platform decisions. Hence there is no switching for either side and agents are bound to their initial choice. Complementors have to decide on a single technology platform and thus cannot 'multi-home'. All technology platforms are available at t=0 and there are no further market entrants. Table 8-4 summarizes the experimental setup and shows the factors and factor levels, as well as the variables that are held constant. All remaining model parameters are fixed at their empirically calibrated values (see Table 7-7).

Table 8-4 Base case experiment setup

Factors		*Min*	*Max*	*Step*	*Factor levels*
$U^{nwkeffect}$	Relative network effect	0.0	0.295	0.295	2
$P^{qualdiff}$	Variation in platform quality	0.0	0.678	0.678	2
Constant variables		*Value*	*Description*		
$U^{infolevel}$	Information level	1.0	Complete information		
$U^{ratiolevel}$	Rationality level	1.0	Perfect rationality		
$U^{horizon}$	Decision horizon (users)	1.0	No switching		
$C^{synlevel}$	Synergy level	0.0	Single-homing only		
$C^{horizon}$	Decision horizon (complementors)	1.0	No switching		
$P^{timediff}$	Entry timing difference	0.0	Simultaneous market entry at t=0		
Simulation runs					
Design points:	4	Total runs:		6,000	
Repetitions:	1,500	Total runtime:		00h:54m:13s	

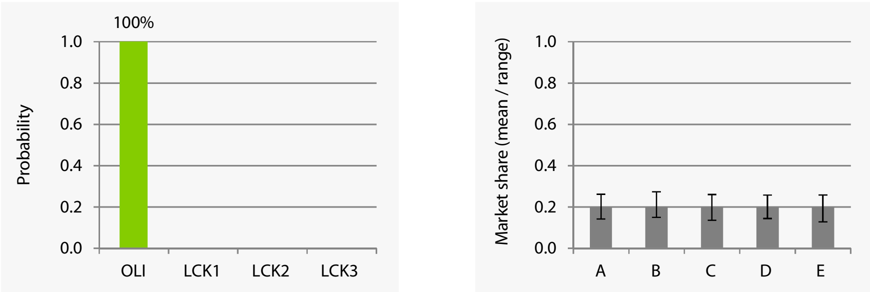
8.3.1 Arthur's model revisited: No differences in quality

The model behavior is first explored in the case of equal platform quality ($P^{qualdiff}$ = 0). Following the assumptions of Arthur's model, none of the technology platforms is defined superior or inferior to others.

Constant returns

In the case of constant returns, there is no indirect network effect ($U^{nwkeffect}$ = 0). Figure 8-5 presents the aggregate results of 1,500 repeated runs. It shows the state of the market at the end of the simulation as well as the market shares of the five competing platforms, A to E, expressed as the mean value and the value range, which is calculated as the maximum minus the minimum market share of each platform over all runs.

Figure 8-5 **Base case experiment: equal platform quality under constant returns**
Aggregate results of 1,500 runs



In the absence of indirect network effects, self-reinforcement does not occur. As such, under constant returns the decisions of individual agents do not impact the decisions of other agents. Because none of the platforms is inferior or superior to the others, all agents choose their technology platform completely randomly. As a result, the market is equally shared by all five competing platforms, each having an average market share of 20 percent. Due to the random nature of the selection process, the market share distribution of individual runs fluctuates slightly around the mean of 20 percent, as shown by the range of market shares in the range of 14 to 27 percent.[152] To conclude, all five platforms coexist in the long run. The probability for an oligopoly market outcome equals 100 percent, and lock-ins to a single technology platform can be ruled out with certainty. This scenario resembles the constant returns case in Arthur's model (1989). The market is shared by all competing technologies, and the outcome is predictable and efficient.

Increasing returns

In the case of increasing returns, indirect network effects influence the interdependent choices of users and complementors. In the experiment, the magnitude of the effect is set to the empirically calibrated value ($U^{nwkeffect}$ = 0.295). Figure 8-6 provides the aggregate results of 1,500 repeated runs.

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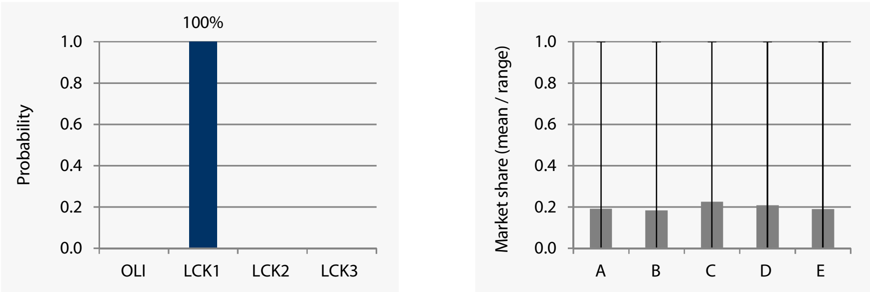
152 Please note that this interval denotes the total range, including outliers, instead of confidence intervals.

Figure 8-6 **Base case experiment: equal platform quality under increasing returns**
Aggregate results of 1,500 runs

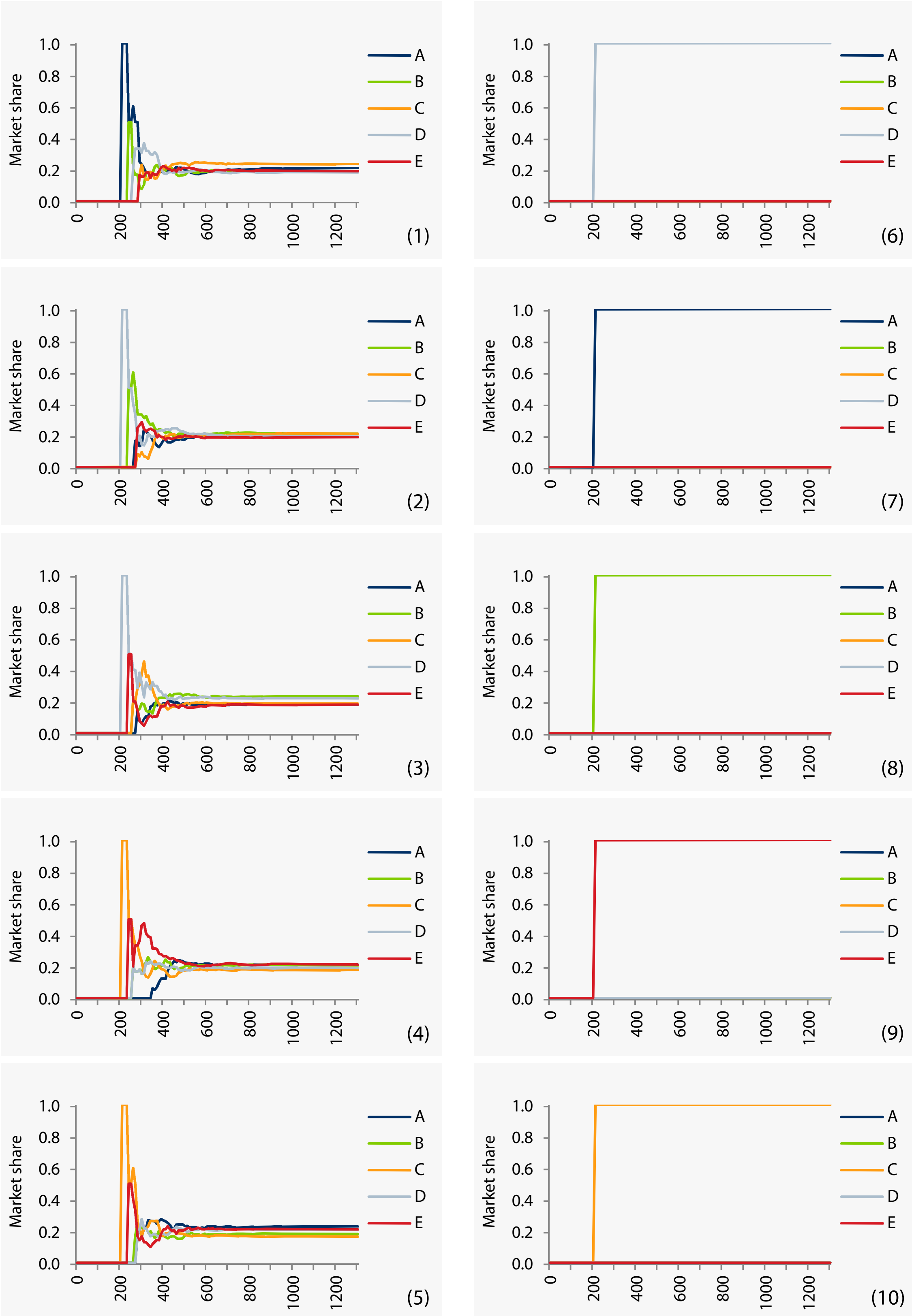


In this setting, the platform choice in the initial phase of the process is again random, because none of the platforms is inferior or superior to the others. However, early decisions by individual agents trigger self-reinforcing dynamics: complementors support the platform that randomly gained an initial lead. As a result, indirect network effects reinforce any small advantage in market share and the market locks in to this particular technology platform. Referring to the aggregate results, the probability for a first-degree lock-in equals 100 percent. However, given that all platforms are of equal quality, it cannot be predicted ex ante *which* platform will dominate the market. Each platform has a final market share of 100 percent in about one-fifth of all runs and a market share of zero percent in the remaining four-fifths of the runs. Accordingly, the mean market share for each platform is again approximately 20 percent, however in this case with a large dispersion between zero and one.

This scenario resembles the increasing returns case of Arthur's model. Ex ante, it can be predicted that the market will lock in to a single technology, but it is unknown which platform will take the market. This scenario inherits the maximum "degree of historicity" (David 1997, p. 27): the random decision of the first agent is the 'small event' that completely determines the dynamic process. Given that all agents are perfectly rational and that the inherent quality of all platforms is equal, even a marginal network effect in favor of a particular platform induces all other adopters to choose the same. To conclude, the market locks in to a single technology with certainty. None of the technology platforms is inferior to the others. Since it has no inherent inefficiency claim, this type of lock-in is termed first-degree.

In order to provide a better understanding of the aggregate results of the model, I also present the market share dynamics of individual simulation runs under constant and increasing returns. All other conditions are identical. The different curves represent the market share of the five platforms A to E over time.

Figure 8-7 **Base case experiment: market share dynamics in the case of equal platform quality**
Constant returns, five illustrative runs (left hand side: 1-5);
increasing returns, five illustrative runs (right hand side: 6-10)



Under constant returns (runs 1-5), the market share of each platform approaches 20 percent in the long run. Given that the agents gradually enter the market, decisions of individual actors have a large impact on the relative market share in the early phase of the process. This explains the substantial fluctuations up to t=500.

Under increasing returns (runs 6-10), the market immediately locks in to a single technology platform as soon as the first agents enter the market around t=200. However, it cannot be predicted ex-ante which platform will take the market in individual simulation runs.

In summary, the base case scenario of this model resembles the results of Arthur (1989). Lock-in occurs only under the condition of increasing returns. In the assumed case of perfect rationality, a contingent lead in adoption is directly reinforced by indirect network effects and leads to an immediate lock-in. The maximum 'degree of historicity' in this scenario is equivalent to an absorbing barrier of close to zero in Arthur's model (see d_A, d_B in Figure 2-2 in section 2.1.2). However, given the assumption that all technology platforms are of equal quality, no conclusions can be drawn on the dominance of *inferior* technologies.

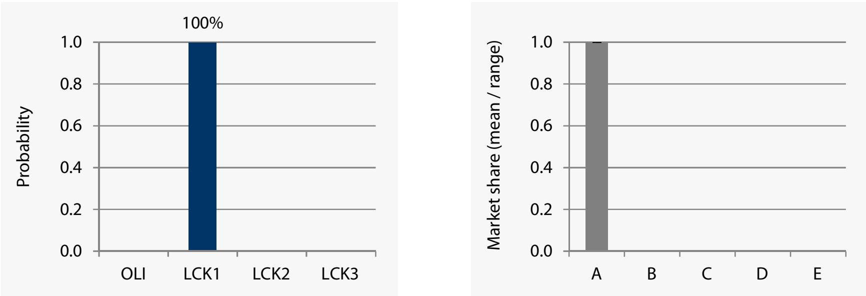
8.3.2 Introducing quality differences

I now abandon the assumption of equal platform quality and introduce quality differences between the competing platforms. On the basis of the empirical calibration (P^{qualdiff} = 0.678), the platforms vary in their inherent quality: platform A is the best technology and platform E is the worst. All other conditions remain unchanged compared to the previous case, and the model behavior is again explored under constant and increasing returns.

Constant returns

Figure 8-8 shows the aggregate results of 1,500 repeated runs under constant returns.

Figure 8-8 **Base case experiment: platform quality differences under constant returns**
Aggregate results of 1,500 runs

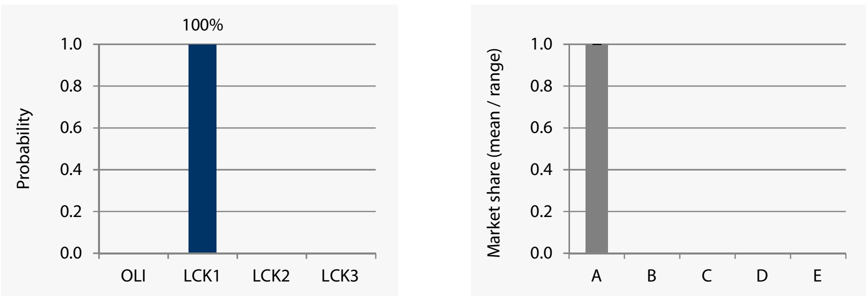


In the case of quality differences between the competing platforms, all agents unsurprisingly choose the best platform A at all times. Given the assumptions of complete information and perfect rationality, they evaluate all platforms in the marketplace and decide for the optimal solution. As a result, platform A dominates the market with a probability of 100 percent in the constant returns case. However, this first-degree lock-in is not inefficient in any meaningful sense.

Increasing returns

The model behavior is now explored in the presence of indirect network effects. Figure 8-9 presents the aggregate results of the increasing returns case.

Figure 8-9 **Base case experiment: platform quality differences under increasing returns**
Aggregate results of 1,500 runs



Introducing self-reinforcement has no additional effect in this setting. The decisions of the fully informed and perfectly rational agents do not change under increasing returns. Both users and complementors continue to choose the optimal platform A, which thus dominates the market in 100 percent of all cases. Again, these results do not contribute much to our understanding of technological lock-ins. In a perfect world, every agent opts for the optimal technology, regardless of the absence or presence of indirect network effects.

Explaining inferior technological lock-ins is at the heart of path dependence theory. The base case experiment emphasizes that increasing returns *alone* do not lead to the dominance of inferior technologies. In addition, the base case highlighted the relationship between the proposed simulation model and existing theoretical contributions. It has been shown that the model resembles the essence of Arthur's model of competing technologies (Arthur 1989). Furthermore, the base case experiment assures that second- and third-degree lock-ins, which describe suboptimal market outcomes, are not 'programmed into the model'. This builds trust in the results that are to come.

8.4 Full calibration experiment

I now abandon the hypothetical assumptions that were used for the base case and turn to the full calibration experiment. In this experiment, all parameter values are fixed at their empirically calibrated values, as summarized in Table 7-7. The fully-calibrated model specification serves as the reference case for all further experiments.

Building on the empirical calibration, the current experiment better reflects platform competition in the real-world: agents act in a boundedly rational manner and possess imperfect information on the competing technology platforms. Both users and complementors reconsider their platform choice in regular intervals and can switch to other platforms. Complementors can multi-home, i.e., they can support multiple platforms if it is beneficial to them. As in the previous scenario, the competing technology platforms differ in quality and indirect network effects influence the interdependent decisions of users and complementors. Following Arthur's assumptions (1989), all technologies are available at t=0 and there are no further market entrants. Table 8-5 summarizes the experiment setup and describes the chosen parameter values.

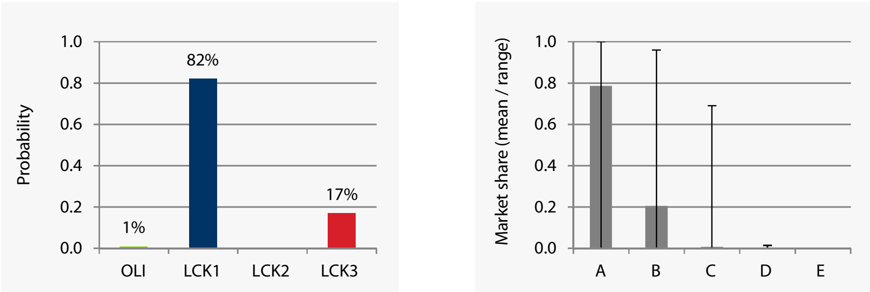
Table 8-5 **Full calibration experiment setup**

Factors		*Min*	*Max*	*Step*	*Factor levels*
-					
Constant variables		*Value*	*Description*		
$U^{infolevel}$	Information level	0.37 *	Imperfect information		
$U^{ratiolevel}$	Rationality level	0.7 *	Bounded rationality		
$U^{nwkeffect}$	Relative network effect	0.295 *	Moderate network effects		
$U^{horizon}$	Decision horizon (users)	0.08 *	Two years		
$C^{synlevel}$	Synergy level	0.3 *	Moderate ease of multi-homing		
$C^{horizon}$	Decision horizon (complementors)	0.04 *	One year		
$P^{qualdiff}$	Variation in platform quality	0.678 *	Medium quality differences		
$P^{timediff}$	Entry timing difference	0.0	Simultaneous market entry at t=0		
Simulation runs					
Design points:	1	Total runs:		1,500	
Repetitions:	1,500	Total runtime:		00h:13m:30s	

* Denotes empirically calibrated parameter values

Figure 8-10 shows the aggregate results of the experiment.

Figure 8-10 **Full calibration experiment**
Aggregate results of 1,500 runs



Compared to the previous experiments, the results exhibit greater variation in the final market outcome. The best platform A dominates the market with a probability of 82 percent (LCK1). However, in 17 percent of all runs, a third-degree lock-in occurs and an inferior platform dominates the market (LCK3). In the remaining one percent of all runs, there is no lock-in to a single technology platform and several players share the market (OLI).

These results are notable in two ways. First, the experiment clearly shows the contingency inherent in the model which leads to non-deterministic simulation results. Running the model multiple times with the *same* parameter values yields *different* market outcomes: even if the initial conditions are known, the outcome of the path-dependent process remains unpredictable ex-ante. Second, the experiment demonstrates that a third-degree lock-in in two-sided markets is indeed possible, following the theoretical assumptions of the model and the empirical calibration of the model parameters. In 17 percent of all cases, an inferior technology dominates the market. This third-degree lock-in is not only suboptimal, but also inefficient. The market locks in to an inferior platform although the optimal platform A was available from the very beginning. Therefore, any suboptimal market outcome is remediable and thus inefficient.

These striking results raise several important questions. Why do inferior lock-ins occur at all? Which factors of influence favor or prevent the dominance of a single technology platform? And which conditions increase or decrease the probability for an inefficient third-degree lock-in? In order to answer these questions, the effects of changing the model parameters are now tested in a number of variation experiments. Following the potential factors of influence for technological path dependence that have been identified in chapter three, four counterfactual experiments are carried out that explore (1) the impact of the strength of indirect network effects and differences in platform quality, (2) the effect of imperfect information and bounded rationality, (3) the influence of switching, and (4) the role of multi-homing.

8.5 Experiment 1: Strength of network effects and differences in platform quality

This experiment explores the impact of the strength of the indirect network effect as well as the influence of quality differences between the competing platforms on the probability for a technological lock-in. Both model parameters are systematically varied to analyze the causal relationships between the proposed factors of influence and the model behavior, including potential interaction effects between the two factors. Table 8-6 summarizes the setup of the simulation experiment.

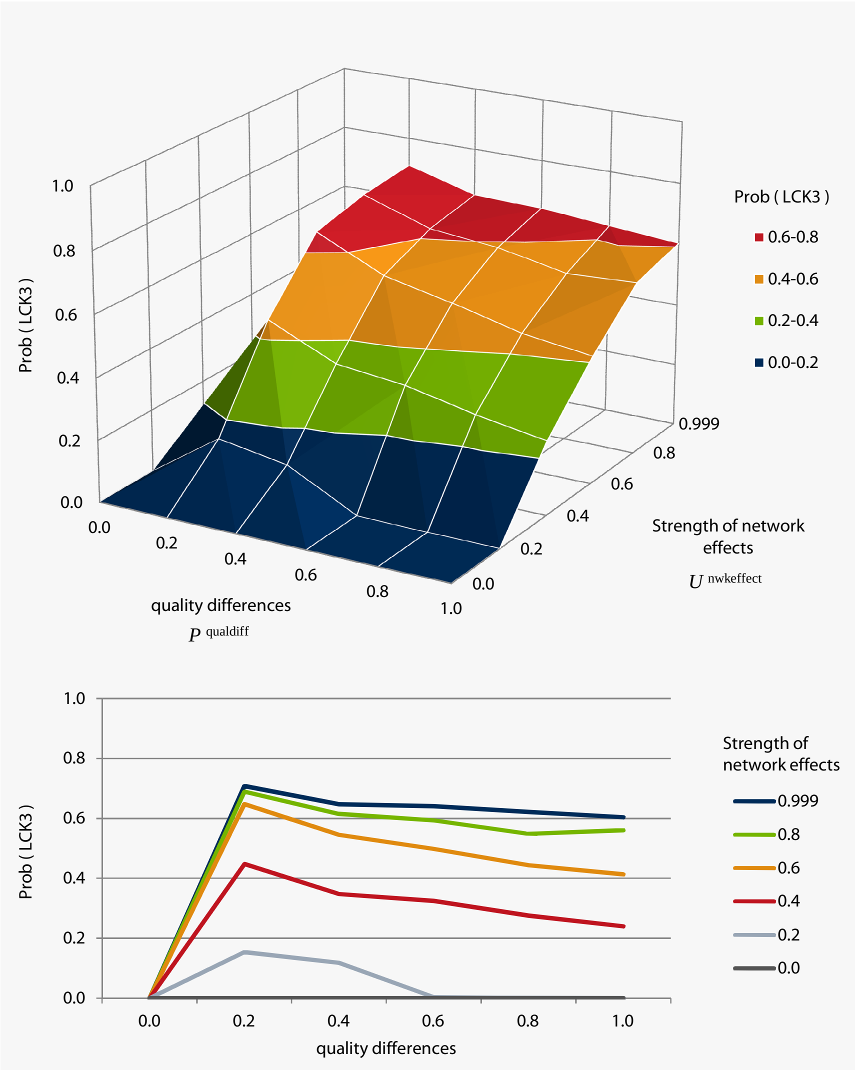
Table 8-6 Experiment 1 setup

Factors		*Min*	*Max*	*Step*	*Factor levels*
$U^{nwkeffect}$	Relative network effect	0.0	1.0	0.2	6
$P^{qualdiff}$	Variation in platform quality	0.0	1.0	0.2	6
Constant variables		*Value*	*Description*		
$U^{infolevel}$	Information level	0.37 *	Imperfect information		
$U^{ratiolevel}$	Rationality level	0.7 *	Bounded rationality		
$U^{horizon}$	Decision horizon (users)	0.08 *	Two years		
$C^{synlevel}$	Synergy level	0.3 *	Moderate ease of multi-homing		
$C^{horizon}$	Decision horizon (complementors)	0.04 *	One year		
$P^{timediff}$	Entry timing difference	0.0	Simultaneous market entry at t=0		
Simulation runs					
Design points:	36	Total runs:		54,000	
Repetitions:	1,500	Total runtime:		08h:06m:47s	

* Denotes empirically calibrated parameter values

Figure 8-11 provides the aggregate results of 54,000 runs. The probability for a third-degree lock-in, defined as the persistent market dominance of an inferior platform, serves as the dependent variable.

Figure 8-11 **Experiment 1: probability for a third-degree lock-in**
Effects of the strength of network effects and platform quality differences; aggregate results of 54,000 runs



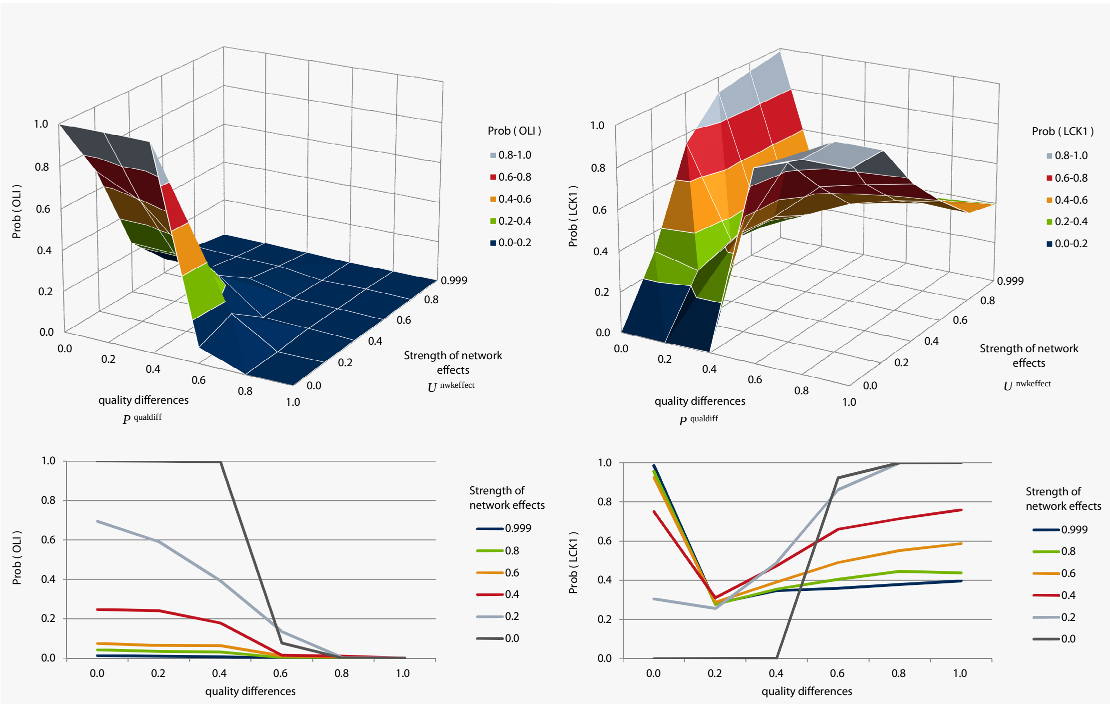
In both charts above, the Y-axis indicates the probability for a third-degree lock-in. The X-axis shows the difference in platform quality, ranging from zero (no differences) to one (large differences). In the upper 3D surface chart, the Z-axis depicts the relative strength of the indirect network effects, ranging from zero (no network effects) to close to one (maximum network effects). The line chart below is based on the same data. Different lines represent different levels of network effects and correspond to different points on the Z-axis in the 3D surface chart.

First, the data shows that the probability for a third-degree lock-in is zero in the case of equal platform qualities ($P^{\text{qualdiff}} = 0$), irrespective of the strength of the network effects. This result seems obvious: with no quality differences, none of the platforms is superior or inferior to the others, and none of the possible market outcomes can be considered as an inefficient third-degree lock-in.

With the inclusion of quality differences, the results become more meaningful with regard to theory. The data indicates that small differences in platform quality (e.g., $P^{\text{qualdiff}} = 0.2$) increase the probability for suboptimal market outcomes. This effect is reinforced by indirect network effects. The smaller the differences in platform quality and the stronger the network effects, the more likely an inefficient third-degree lock-in to an inferior platform becomes. When the network effects are weak and the quality differences between the platforms are high, a lock-in to an inferior technology becomes rather unlikely.

In the present case of simultaneous market entry, the market state at the end of the simulation can either be an oligopoly (OLI), a first-degree lock-in (LCK1) or a third-degree lock-in (LCK3). By definition, the sum of the probabilities for each of the three possible states equals one. Since the probability for a third-degree lock-in has already been presented in Figure 8-11, a further analysis of the data with regard to the other two possible market outcomes (OLI / LCK1) reveals further insights into the model behavior (see Figure 8-12).

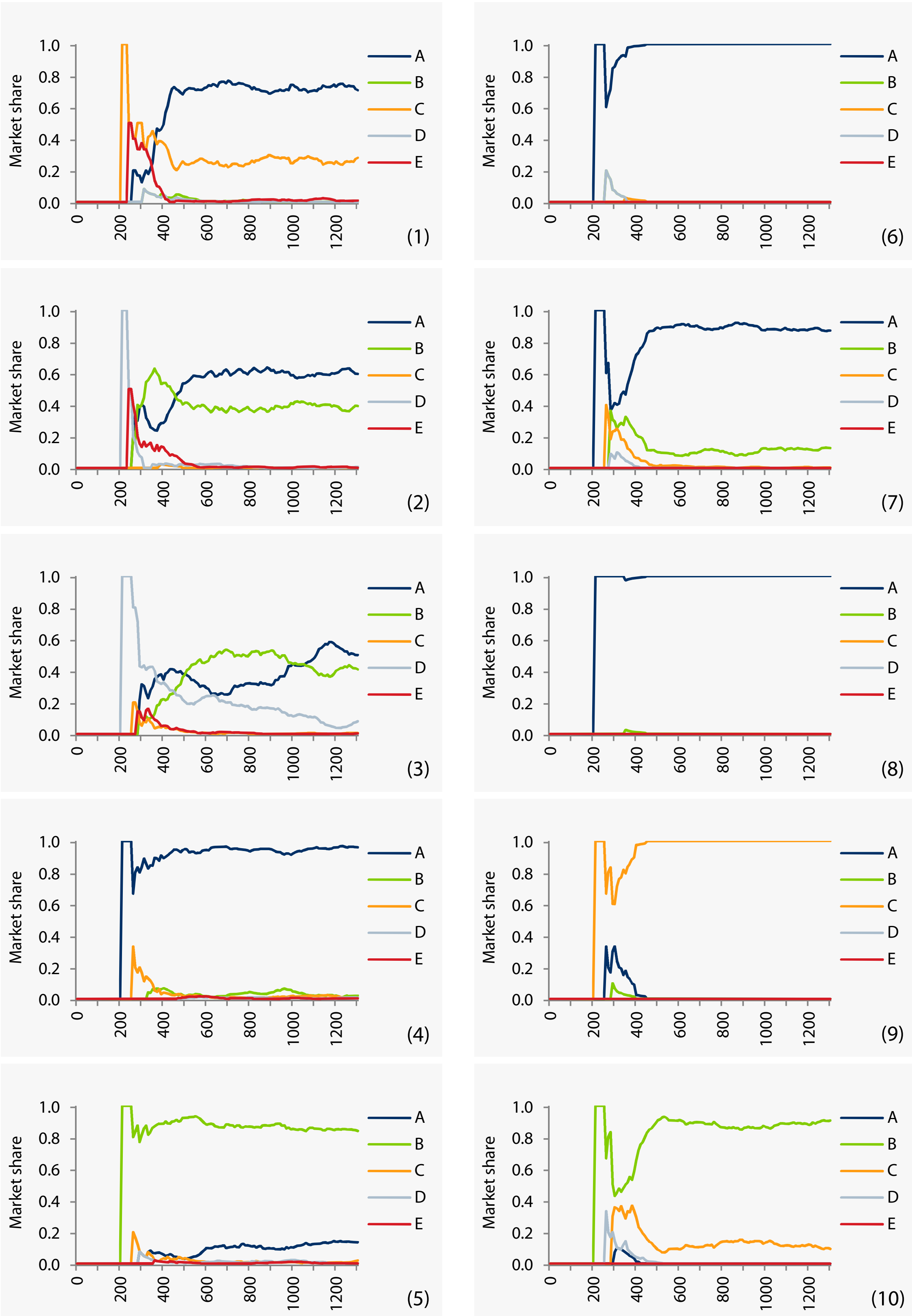
Figure 8-12 **Experiment 1: probability for an oligopoly/a first-degree lock-in**
Effects of the strength of network effects and platform quality differences; aggregate results of 54,000 runs



In the case of marginal quality differences and weak network effects, several technology platforms coexist in the long run (see left chart in Figure 8-12). In the case of larger quality differences and weak network effects, the market tips to the optimal platform with certainty (see right chart in Figure 8-12). Under strong indirect network effects, either a first-degree lock-in or an inefficient third-degree lock-in occurs. In any case, a single technology platform dominates the market. This finding confirms the argument by Evans & Schmalensee (2008) that the strength of indirect network effects is positively related with industry concentration in two-sided markets.

The analysis of individual simulation runs facilitates a deeper understanding of the model behavior. Figure 8-13 presents the market share dynamics of ten illustrative runs. Two different model specifications with five repeated runs each are compared.

Figure 8-13 **Experiment 1: market share dynamics**
Marginal quality differences and weak network effects (left hand side: runs 1-5); large quality differences and strong network effects (right hand side: runs 6-10)



Runs 1-5 demonstrate the model behavior in the case of marginal quality differences (P^{qualdiff} = 0.2) and weak indirect network effects ($U^{\text{nwkeffect}}$ = 0.2). In all cases, several platforms coexist in the long run. The best platform A usually gains the highest market share but does not completely dominate the market (OLI, runs 1-3). In rare cases, the same initial conditions ultimately result in the dominance of the best platform (LCK1, run 4) or even the dominance of an inferior platform (LCK3, run 5).

Runs 6-10 present the market dynamics in the case of large quality differences (P^{qualdiff} = 0.8) and strong indirect network effects ($U^{\text{nwkeffect}}$ = 0.8). In this scenario, it is highly probable that the market locks in to a single platform. In general, the best platform prevails (runs 6-8), however lock-ins to inferior platforms are also possible (runs 9-10).

To conclude, technological path dependence is heavily influenced by quality differences and the magnitude of network effects. Under strong network effects, the market tips to one technology, but not necessarily to the optimal one. Who is responsible for the misallocation in this latter case? Given that all platforms are available right from the start, why do agents choose inferior platforms at all? The following simulation experiment will address these questions.

8.6 Experiment 2: Imperfect information and bounded rationality

This experiment explores the effect of bounded rationality and imperfect information. Both potential factors of influence are systematically varied to analyze the change in model behavior. As before, all other model parameters are fixed at their empirically calibrated values. Table 8-7 summarizes the setup of the simulation experiment.

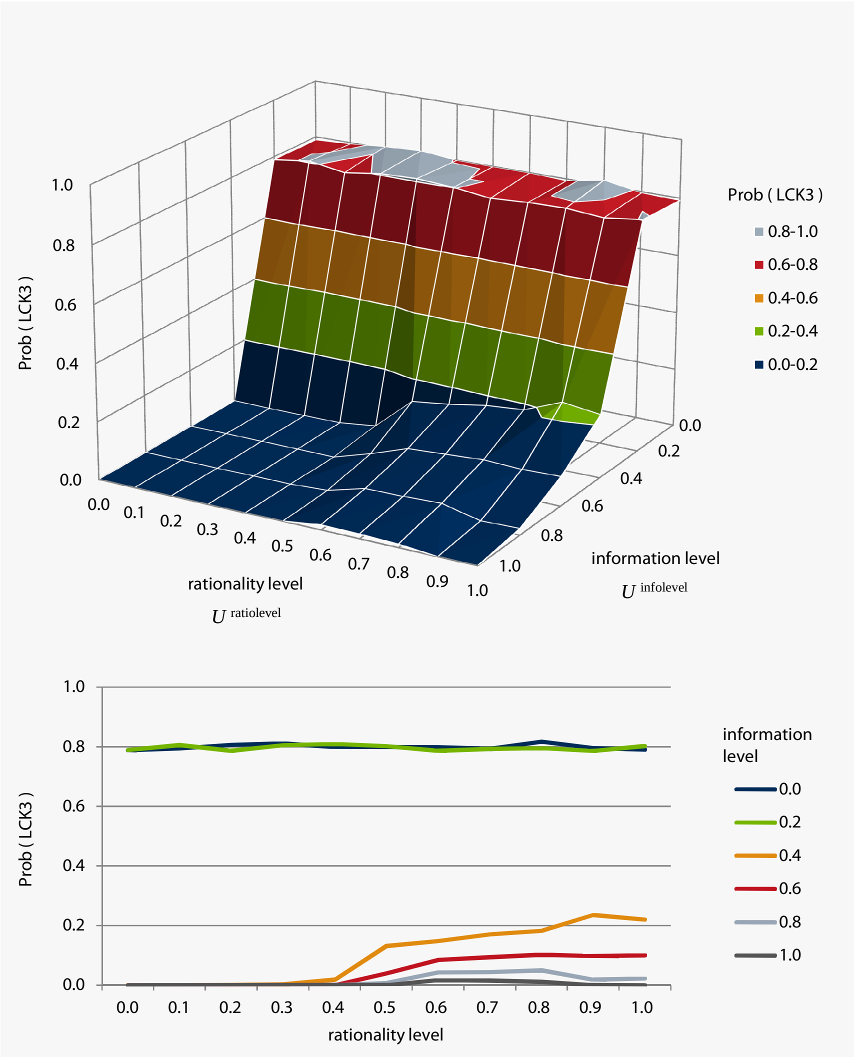
Table 8-7 Experiment 2 setup

Factors		*Min*	*Max*	*Step*	*Factor levels*
$U^{infolevel}$	Information level	0.0	1.0	0.2	6
$U^{ratiolevel}$	Rationality level	0.0	1.0	0.1	11
Constant variables		*Value*	*Description*		
$U^{nwkeffect}$	Relative network effect	0.295 *	Moderate network effects		
$U^{horizon}$	Decision horizon (users)	0.08 *	Two years		
$C^{synlevel}$	Synergy level	0.3 *	Moderate ease of multi-homing		
$C^{horizon}$	Decision horizon (complementors)	0.04 *	One year		
$P^{qualdiff}$	Variation in platform quality	0.678 *	Medium quality differences		
$P^{timediff}$	Entry timing difference	0.0	Simultaneous market entry at t=0		
Simulation runs					
Design points:	66	Total runs:		99,000	
Repetitions:	1,500	Total runtime:		14h:51m:05s	

* Denotes empirically calibrated parameter values

Figure 8-14 presents the aggregate results of 99,000 simulation runs. The probability for a third-degree lock-in, defined as the persistent market dominance of an inferior platform, serves as the dependent variable.

Figure 8-14 **Experiment 2: probability for a third-degree lock-in**
Effects of the information level and rationality level; aggregate results of 99,000 runs



In both charts, the Y-axis indicates the probability for a third-degree lock-in. The X-axis shows the rationality level of consumer agents, ranging from zero (very irrational) to one (perfectly rational). In the 3D surface chart, the Z-axis depicts the information level of consumers, ranging from one (complete information) to zero (very little information). The line chart is based on the same data. Different lines represent different information levels, corresponding to different points on the Z-axis in the 3D surface chart.

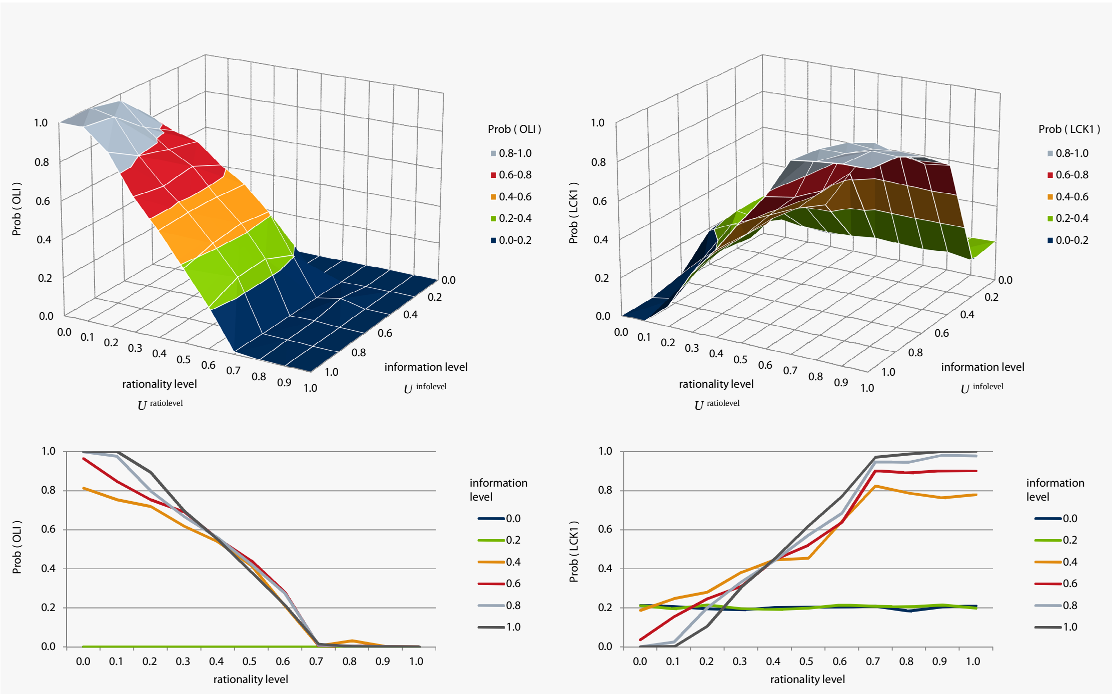
First, the data shows that under complete information and perfect rationality (depicted in the front right-hand corner of the surface chart), there is no probability for a third-degree lock-in. Agents have complete information on all competing platforms and include all possible alternatives in their consideration set. They act perfectly rational and can fully assess the qualities of the technology platforms. As a result, all agents choose the optimal platform A and a third-degree lock-in to an inferior platform is impossible. These simulation results confirm the findings by Casari on the heterogeneity of identical but boundedly rational agents: "at the limit case of full rationality, the outcome converges to the standard result of uniform individual behavior" (Casari 2003, p. 1).

Second, the data shows that lower information levels correspond to a higher probability of third-degree lock-ins. When agents have very little information ($0 \leq U^{\text{infolevel}} \leq 0.2$)[153], they receive this limited information completely by means of word of mouth from other adopters. Wrong platform decisions in the very beginning of the diffusion process propagate in the social network and have a particular, long-lasting influence on the market outcome. In general, the effect size of imperfect information seems to be higher than the impact of bounded rationality.

Third, it can be seen that the influence of the rationality level heavily depends on the information level: both factors interact. In the case of very limited information, the rationality level has no further impact. A third-degree lock-in is the common market outcome, triggered by considerable information deficits. In the most extreme case of complete information, the lock-in to an inferior platform remains a very rare phenomenon with a probability of less than five percent, and only occurs in combination with medium to high rationality levels ($0.6 \leq U^{\text{ratiolevel}} \leq 0.8$). In the case of complete information, low levels of rationality ($U^{\text{ratiolevel}} < 0.6$) as well as very high levels of rationality ($U^{\text{ratiolevel}} > 0.8$) prevent third-degree lock-ins. In the case of medium information levels, it is interesting to see that *more* rationality increases the probability for an inefficient third-degree lock-in (LCK3). In order to better understand this bewildering effect, I analyze the experimental data with regard to the other two possible market outcomes (OLI/LCK1).

153 It should be noted though that $U^{\text{infolevel}} \leq 0.2$ is a rather extreme assumption.

Figure 8-15 **Experiment 2: probability for an oligopoly/a first-degree lock-in**
Effects of the information level and rationality level;
aggregate results of 99,000 runs



When agents act very irrationally, they randomly decide on their platform choice instead of carefully evaluating the benefits and shortcomings of the available technology platforms. In combination with high information levels, several platforms hold considerable market share. Under these conditions, complementors adopt a multi-homing strategy. Therefore, multiple platforms benefit from indirect network effects and coexist in the long-run. As a result, an oligopoly is the most frequent market outcome, as can be seen in the front left-hand corner of the left chart in Figure 8-15.

When agents are well informed about all the competing technology platforms and also behave very rationally, they recognize the optimal platform with certainty. This situation is shown in the front right-hand corner of the right chart in Figure 8-15. Complementors concentrate their development effort on this platform and a first-degree lock-in is very likely to result.

I have already emphasized that in the case of medium information levels, *more* rationality increases the probability for an inefficient third-degree lock-in. The presentation of the data in Figure 8-15 helps to understand this counterintuitive effect. For illustrative purposes, let us imagine the case of only two technology platforms A and B, where B is inferior to A. Let us assume that B has, by chance, gained an initial lead in adoption, for instance because some early adopters had limited information about the superiority of platform A. As a consequence, complementors focus their development effort on platform B, which soon benefits from a large portfolio of complementary products. Thanks to the indirect network effects, platform B becomes the 'best' choice from an aggregate utility perspective. Thus, *rational* users strictly prefer platform B over A, although platform A is of higher inherent quality. Ultimately, the market tips towards platform B and a third-degree lock-in occurs. However, in the case where users are less rational, some agents will 'accidently' choose platform A. As a consequence of this 'irrational choice', platform A gains some market share and becomes supported by multi-homing complementors. Both platforms now benefit from indirect network effects. Over time, the portfolios of compatible products become comparable in size and the distinct lead in adoption of platform B disappears. In the described setting, bounded rationality hinders the positive feedback processes that otherwise would lead to the dominance of an inferior technology platform. Put differently, although counterintuitive, more rationality increases the probability for third-degree lock-ins in specific settings.[154] This highlights the interaction between agents' rationality and their information level.

To conclude, both limitations of knowledge and limitations of computational capacity can induce poor platform choices. Agents either do not include the optimal platform in their consideration set or they do not recognize its superiority. The results confirm that, in most settings, these mistakes by individual agents are "averaged away and 'forgotten' by the dynamics" (Arthur 1989) of the competitive process in the simulated market. Thus, incomplete information and bounded rationality *per se* are not harmful in decentralized markets. However, in the early phase of the diffusion process, these suboptimal decisions are reinforced by the actions of complementors. In combination with indirect network effects, incomplete information and bounded rationality may therefore trigger inefficient lock-ins to inferior technology platforms. Furthermore, the simulation has uncovered surprising interaction effects of both factors.

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154 I am grateful for a comment by Giovanni Dosi at the *2nd International Conference on Path Dependence* (March 3-4, 2011 in Berlin) that brought this interpretation of the simulation results to my attention.

8.7 Experiment 3: Switching

The third experiment serves to examine the role of agents' switching behavior. In the model, agents reconsider their platform choice at regular intervals, termed the decision horizon, and may switch to alternative technology platforms. The aim of the experiment is to identify the causal relationship between the decision horizon and the occurrence of technological lock-ins.

First, both the decision horizons of users and complementors are varied over their entire range between zero and one. With a minimum decision horizon of zero, agents instantly reconsider their choices, i.e., after every model time step. With a maximum decision horizon of one, agents are bound to their initial decision indefinitely and cannot switch to other technology platforms. Table 8-8 summarizes the setup of the experiment.

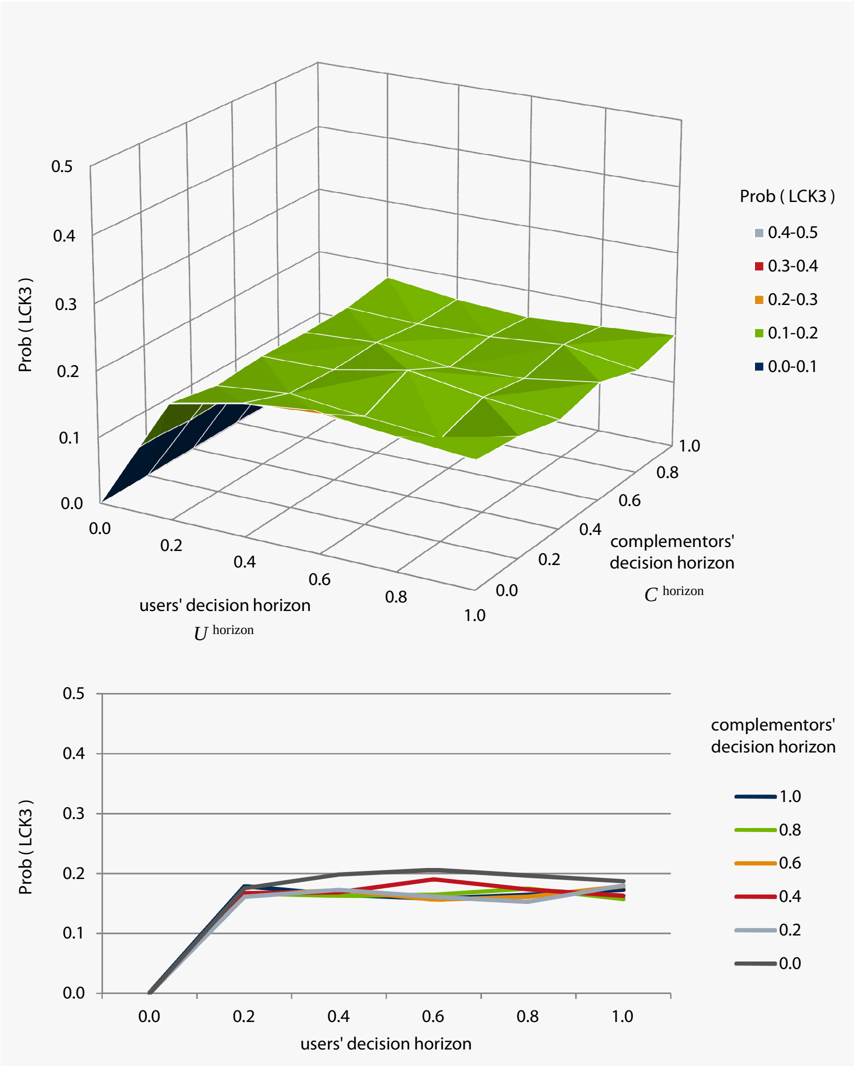
Table 8-8 **Experiment 3 setup**

Factors		*Min*	*Max*	*Step*	*Factor levels*
$U^{horizon}$	Decision horizon (users)	0.0	1.0	0.2	6
$C^{horizon}$	Decision horizon (complementors)	0.0	1.0	0.2	6
Constant variables		*Value*	*Description*		
$U^{infolevel}$	Information level	0.37 *	Imperfect information		
$U^{ratiolevel}$	Rationality level	0.7 *	Bounded rationality		
$U^{nwkeffect}$	Relative network effect	0.295 *	Moderate network effects		
$C^{synlevel}$	Synergy level	0.3 *	Moderate ease of multi-homing		
$P^{qualdiff}$	Variation in platform quality	0.678 *	Medium quality differences		
$P^{timediff}$	Entry timing difference	0.0	Simultaneous market entry at t=0		
Simulation runs					
Design points:	36	Total runs:		54,000	
Repetitions:	1,500	Total runtime:		12h:03m:58s	

* Denotes empirically calibrated parameter values

Figure 8-16 presents the aggregate results of 54,000 runs. The probability for a third-degree lock-in is used as the dependent variable.

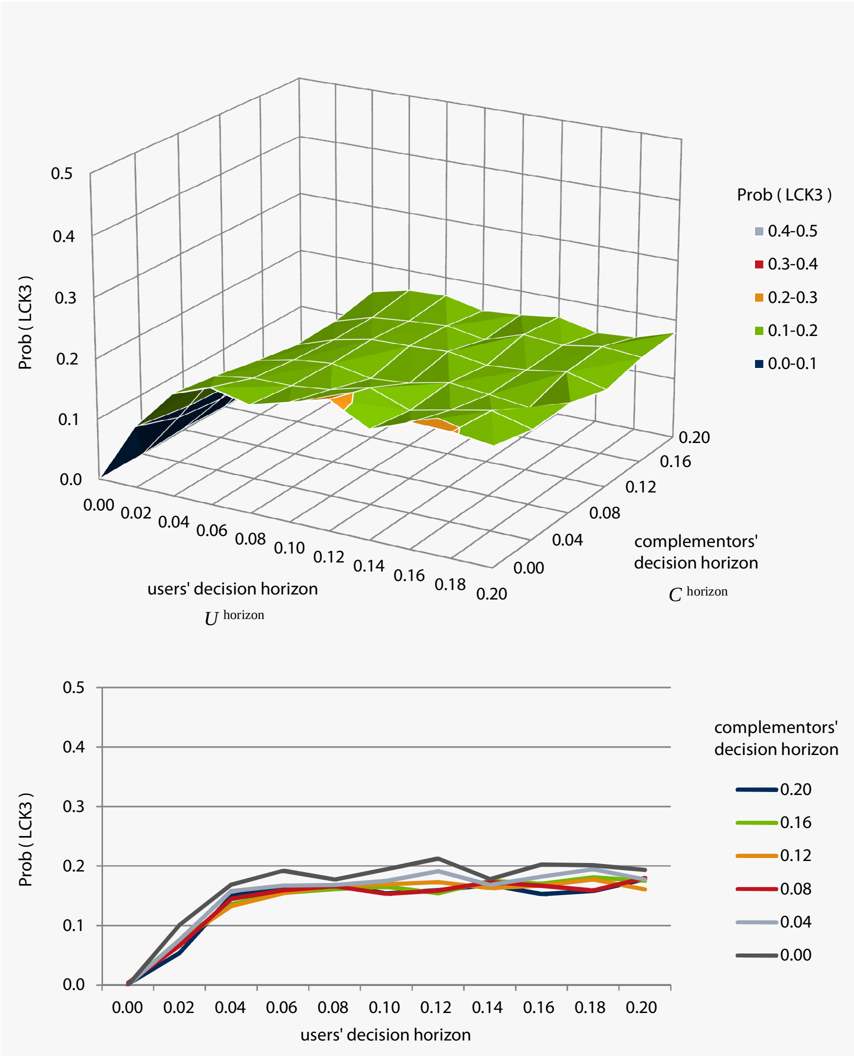
Figure 8-16 **Experiment 3: probability for a third-degree lock-in**
Effects of the decision horizon of users [0, 1] and complementors [0, 1];
aggregate results of 54,000 runs



It is apparent from the data that the complementors' decision horizon does not have a notable effect on the probability for a third-degree lock-in. Furthermore, the decision horizon of users is effective only for values below 0.2. For higher values, the probability of a third-degree lock-in is constant at approximately 17 percent. Accordingly, the results match those of the full calibration experiment.

In order to better focus on the value range of interest, I repeat the simulation experiment while varying both factors between 0 and 0.2. Eleven factor levels are used for users' decision horizon and six factor levels for complementors' decision horizon. Figure 8-17 visualizes the aggregate results of 99,000 runs. As before, the probability for a third-degree lock-in serves as the dependent variable.

Figure 8-17 **Experiment 3-2: probability for a third-degree lock-in**
Effects of the decision horizon of users [0.0, 0.2] and complementors [0.0, 0.2]; aggregate results of 99,000 runs

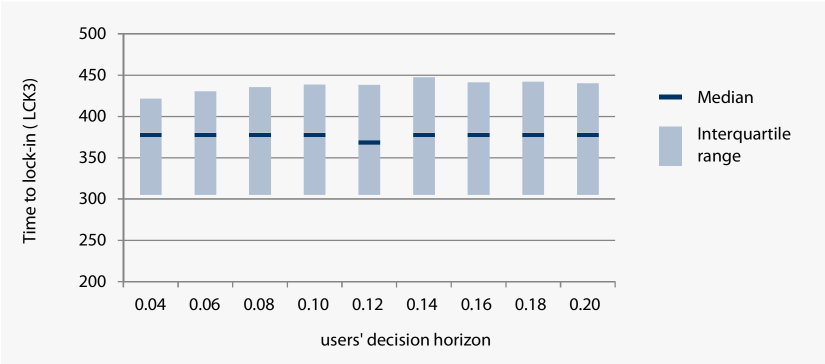


The largely flat surface in the upper chart shows that the probability for an inefficient third-degree lock-in again remains stable at around 17 percent for most of the factor levels. The experiment confirms that the decision horizon of complementors does not seem to have a notable effect, even when testing for very low values. However, the probability for a third-degree lock-in sharply decreases in the case of extremely short decision horizons of users ($U^{horizon}$ < 0.04), equivalent to less than one year in real time. If users reconsider their platform choice either every week (i.e., after every tick, $U^{\text{horizon}} = 0.0$) or every six months ($U^{\text{horizon}} = 0.02$), a lock-in to an inferior technology platform becomes very unlikely. This model behavior can be explained as following: it has already been argued that the market dominance of an inferior platform is the result of erroneous platform decisions by early adopters which are then reinforced by the actions of complementors. In the case of very short decision horizons, agents revise their wrong platform choices *before* the self-reinforcing nature of the indirect network effects magnifies these seemingly insignificant decisions. This effect becomes clear when taking a closer look at the decision-making process of agents. Even with bounded rationality and imperfect information, agents *tend* to select the optimal platform: the expected value, in the statistical sense, of the partly random decision-making process is to choose the best platform.[155] Thus, there is a tendency towards the optimal choice. It follows that the more frequently a decision is reconsidered before self-reinforcement 'kicks in', the less likely an inefficient market outcome is. This explains the fact that very short decision horizons decrease the probability of inefficient lock-ins.

It might be assumed that longer decision horizons would increase the probability for inefficient lock-ins. However, the data shows that this is not the case. In order to better understand this issue, it is interesting to analyze the timing of the lock-in process in detail. Figure 8-18 presents the 'time to lock-in' for different factor levels of users' decision horizon. The aggregate data of the time to lock-in is expressed by the median value and the interquartile range, which are both insensitive to outliers.

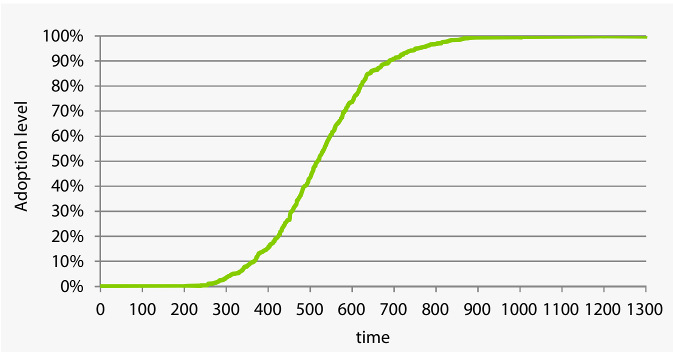
[155] In fact, any other decision heuristic that would specifically favor an inferior platform would be questionable. It would open the model to criticism that the occurrence of inferior market outcomes is 'programmed into the model' instead of being the result of a nonergodic, path-dependent process.

Figure 8-18 **Experiment 3-2: time to lock-in (third-degree)**
Measured in model time steps, median and interquartile range; aggregate results of 99,000 runs



The time to lock-in describes the moment when the market tips in favor of a single platform. The data shows that, if the market locks in at all, it locks in rather quickly. The median value is between t=350 und t=400, independent of the users' decision horizon. To put this finding in perspective, Figure 8-19 displays the simulated adoption timing, which was derived in section 7.3.

Figure 8-19 **Simulated diffusion curve**
Cumulative adoption level over time



As shown, the first agents enter the market approximately at t=200. Experiment 3-2 discovered that the market, on average, locks in around approximately t=375. At this point in time, only about 10 percent of the agents have adopted the innovation. As a consequence, it is the behavior of the early adopters which decides whether a lock-in occurs or not. Against this background it is easy to see why longer decision horizons do not increase the probability for an inefficient lock-in. Imagine the case that the inferior platform B gains an initial lead in adoption in the early phase of the process. Indirect network effects trigger self-reinforcing dynamics and the inferior platform becomes the 'best' choice from an aggregate utility perspective. Because it is now individually rational for current and prospective users to choose platform B, the market tips towards platform B. In this setting, it does not matter whether agents reconsider their platform choice in shorter or longer intervals. The market is already locked in and platform B remains the 'best' choice despite alternative technologies with superior quality. The decision horizon has no further influence.

To conclude, the decision horizon of users and complementors does not play a significant role for the emergence of technological path dependence. Inefficient lock-ins occur, if at all, at a very early stage, since it is only in this phase of the diffusion process that individual decisions may have long-run consequences. When the majority of users enter the market, the decision in favor of a potentially inferior standard has already been made.

8.8 Experiment 4: Multi-homing

Experiment number four focuses on the impact of multi-homing on the probability of technological lock-ins at the market level. Complementors develop complementary products for either one or multiple platforms. They are faced with a trade-off decision between lower market coverage when single-homing or additional development effort when multi-homing. The latter depend on the level of synergies for multi-platform development. High synergy levels make it rather effortless to support multiple technology platforms, whereas low values encourage single-homing strategies. The aim of this experiment is to identify the causal relationship between the level of synergies and the occurrence of lock-in. I also test for possible interaction effects between the synergy level and the strength of network effects. Table 8-9 summarizes the experiment setup.

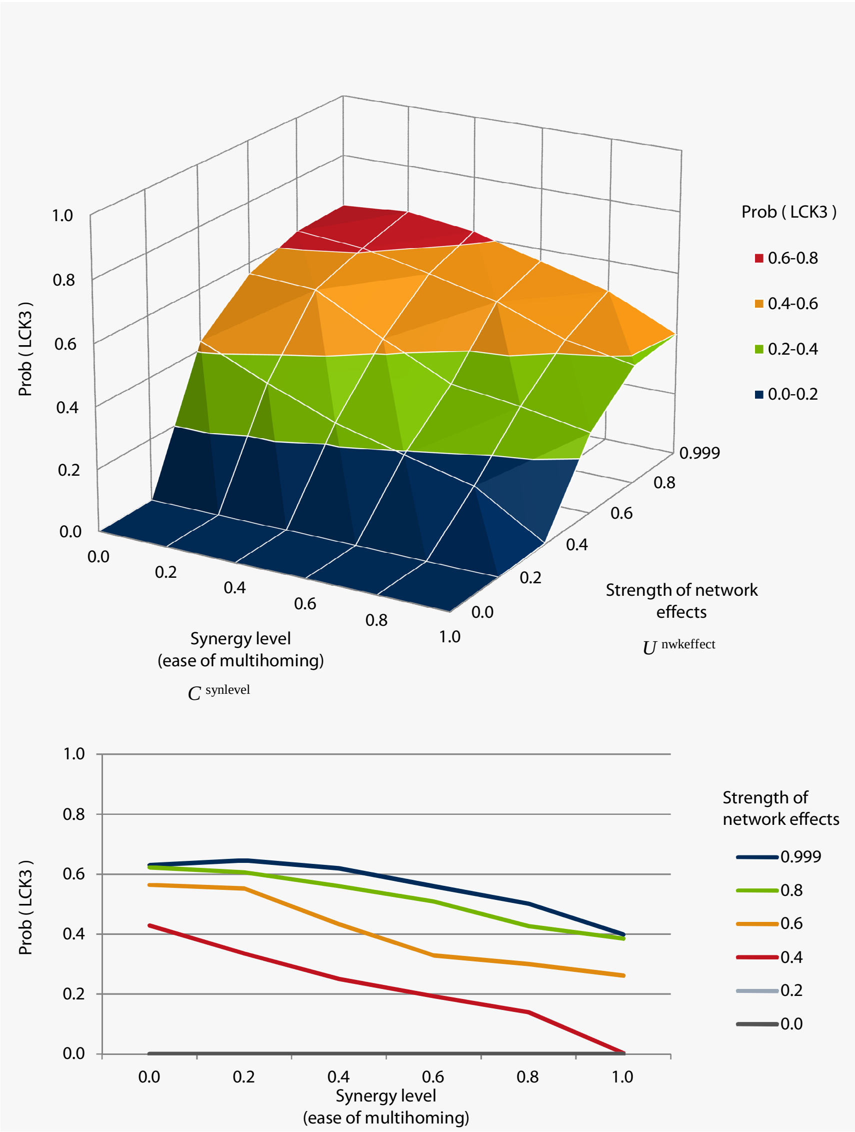
Table 8-9 **Experiment 4 setup**

Factors		*Min*	*Max*	*Step*	*Factor levels*
$C^{synlevel}$	Synergy level	0.0	1.0	0.2	6
$U^{nwkeffect}$	Relative network effect	0.0	1.0	0.2	6
Constant variables		*Value*	*Description*		
$U^{infolevel}$	Information level	0.37 *	Imperfect information		
$U^{ratiolevel}$	Rationality level	0.7 *	Bounded rationality		
$U^{horizon}$	Decision horizon (users)	0.08 *	Two years		
$C^{horizon}$	Decision horizon (complementors)	0.04 *	One year		
$P^{qualdiff}$	Variation in platform quality	0.678 *	Medium quality differences		
$P^{timediff}$	Entry timing difference	0.0	Simultaneous market entry at t=0		
Simulation runs					
Design points:	36	Total runs:		54,000	
Repetitions:	1,500	Total runtime:		07h:54m:00s	

* Denotes empirically calibrated parameter values

Figure 8-20 presents the aggregate results of 54,000 simulation runs. As before, the probability for a third-degree lock-in is used as the dependent variable.

Figure 8-20 **Experiment 4: probability for a third-degree lock-in**
Effects of the synergy level for multi-homing and the strength of network effects; aggregate results of 54,000 runs

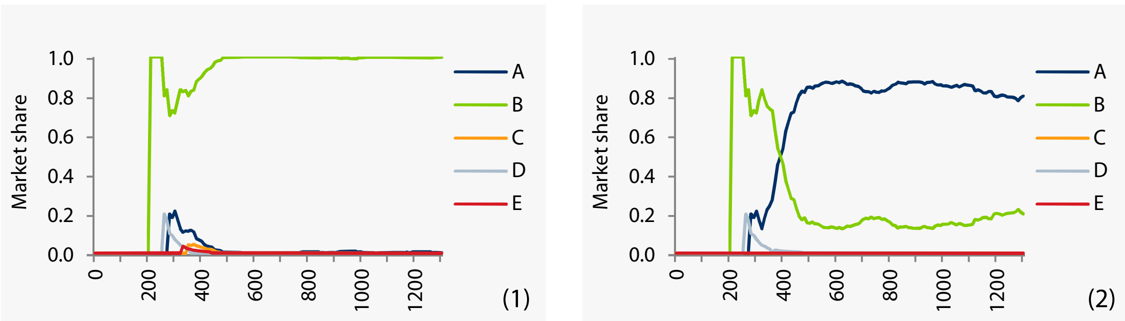


The isolated relationship between the strength of network effects and the probability for lock-in has already been described in the first experiment (section 8.5). Ceteris paribus, the stronger the indirect network effects, the higher the probability for an inefficient lock-in.

Let us now focus on the multi-homing factor. It is apparent that higher synergy levels, which are associated with a greater ease of multi-homing, decrease the probability for a third-degree lock-in. In other words, a higher degree of compatibility between the technology platforms makes it less likely that the market is dominated by an inferior platform. The data shows that interaction effects between both factors can be largely neglected. Except for the case of very weak network effects ($U^{nwkeffect} \leq 0.2$), the influence of the synergy level exists for all levels of network effects.

The influence of the multi-homing factor can be best demonstrated by analyzing one illustrative simulation run in detail. The aim is to compare the model behavior in the case of single- and multi-homing under otherwise identical conditions. It has already been emphasized that running the simulation model multiple times with identical parameter settings will produce different market outcomes. This highlights the contingent nature of path-dependent processes, but makes it virtually impossible to compare individual runs. However, social simulation provides the genuine advantage that the researcher can control for the influence of randomness. It allows one to create *reproducible* experiments with *stochastic* models when necessary.[156] Thus, *repeated* simulation runs can exhibit the *identical* random behavior. In this way, the influence of multi-homing can be analyzed in isolation under otherwise identical conditions. Figure 8-21 compares the competition dynamics of one illustrative simulation run in the case of single-homing ($C^{synlevel} = 0$) and multi-homing ($C^{synlevel} = 0.8$).

Figure 8-21 **Experiment 4-2: market share dynamics in the cases of single- and multi-homing**
Single-homing (left) vs. multi-homing (right) under otherwise identical conditions; a fixed random seed guarantees the identical stochastic behavior of the model



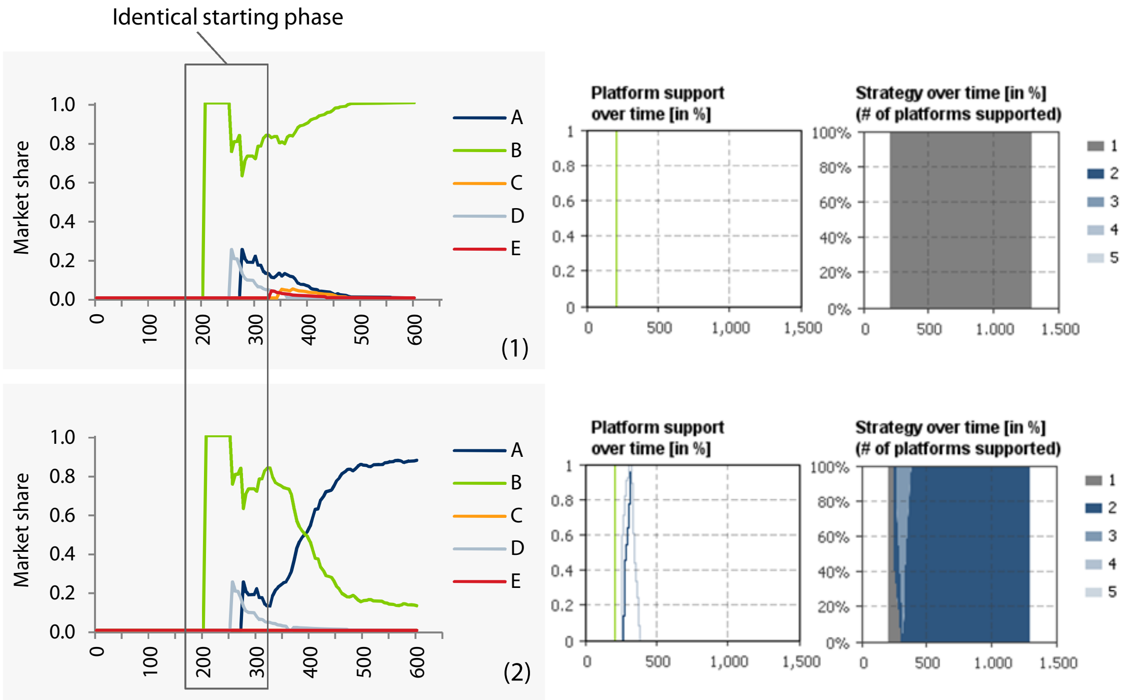
In the case of single-homing (run 1), the inferior platform B dominates the market: a third-degree lock-in occurs. In the case of multi-homing (run 2), platform B also gains an initial lead, however the market later tips to the optimal platform A. Given that all random effects have been

[156] Computers rely on pseudo-random number generators that produce apparently random results starting from an initial 'seed value'. Using a custom random number generator with a constant seed value makes it possible to conduct reproducible stochastic experiments.

disabled for the experiment, this difference in model behavior must be attributed to the change of the synergy level parameter.

I analyze both runs in more detail by taking a closer look at the initial phase of the diffusion process. In addition to the market share dynamics, I also examine the platform strategies of the complementors over time.

Figure 8-22 **Experiment 4-2: a closer look at the effect of multi-homing**
Single-homing (top) vs. multi-homing (bottom) under otherwise identical conditions; a fixed random seed guarantees the identical stochastic behavior of the model



The two simulation runs proceed identically up to time t=350. By chance, platform B gains an initial lead in adoption and quickly dominates the market. However, platforms A and D also have considerable market shares of 10 to 20 percent. In the single-homing case (run 1), the complementors fully concentrate their development effort on the most successful platform B. Indirect network effects exclusively benefit platform B, which over time becomes even more attractive in relation to the other competing platforms. Ultimately, the contingent lead in adoption results in the long-run dominance of platform B: a third-degree lock-in occurs.

In the multi-homing case (run 2), the complementors not only support the leading platform B, but also support other platforms with smaller market share. As a result, the superior platform A also benefits from the development of complementary products and platform B cannot expand its market lead. Over time, agents recognize the superiority of platform A. In most cases, new adopters immediately choose the optimal platform A. Early adopters that have already chosen platform B gradually switch to A. As a result, the superior platform A takes over the market between time t=350 und t=500. Platform B manages to stay in the market, though with a small market share of less than 20 percent. Complementors support both platforms in the long run.

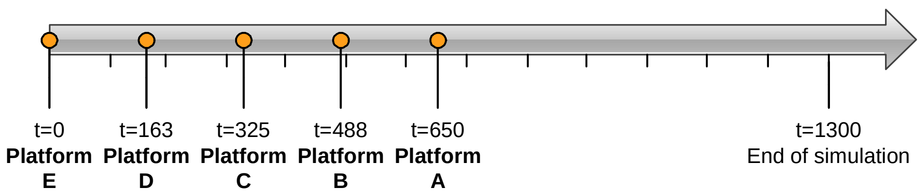
To conclude, higher synergy levels encourage complementors to pursue multi-homing strategies. As a result, the market-driven selection process remains open for a longer period of time and alternative technologies are not as easily locked out. The market is less affected by initial decisions of individual actors and is thus more likely to select the optimal choice. In summary, high synergy levels facilitate multi-homing and thereby reduce the probability for the dominance of inferior technology platforms.

8.9 Full calibration experiment with successive market entry

In line with the assumptions of Arthur's model (Arthur 1989), all experiments have so far analyzed platform competition in the case where all platforms *simultaneously* enter the market. However, in reality it more often happens that superior technology platforms *successively* enter the market and challenge the incumbent platforms. In these settings, the market outcome is difficult to predict. On the one hand, incumbents benefit from their existing installed base, which gives rise to indirect network effects that may help them to retain market leadership despite their technological inferiority. On the other hand, new entrants possess better quality, which may drive their success. The question is now whether the market locks in to an inferior first-mover or whether it favors superior new entrants.

To address this question, this experiment explores platform competition in the case of successive market entry. Given that late entrants benefit from technological progress and longer development times, it is assumed that they possess better quality than incumbent platforms. Furthermore, it is assumed that agents do not anticipate the market entry of new platforms. As such, the availability of novel technology platforms acts as external shocks to the system, outside the ex-ante knowledge of the agents. The experiment setup is identical to the previous full calibration experiment in section 8.4, except for the entry timing behavior. For the present experiment, the entry timing parameter is set to a medium value of 0.5. Figure 8-23 illustrates the entry timing of the competing technology platforms.

Figure 8-23 Entry timing of competing technology platforms



As can be seen, the worst platform E is the first to enter the market at t=0. The best platform A enters last at t=650. All other model parameters are fixed at their empirically calibrated values. Table 8-10 summarizes the experiment setup.

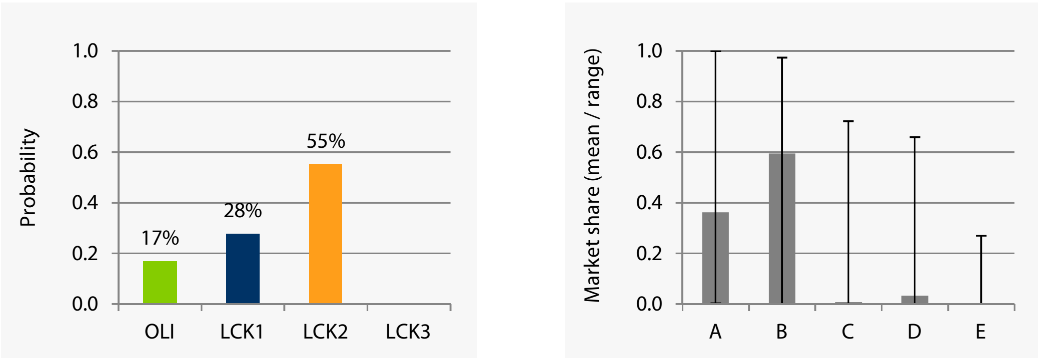
Table 8-10 Full calibration experiment setup with successive market entry

Factors		*Min*	*Max*	*Step*	*Factor levels*
-					
Constant variables		*Value*	*Description*		
$U^{infolevel}$	Information level	0.37 *	Imperfect information		
$U^{ratiolevel}$	Rationality level	0.7 *	Bounded rationality		
$U^{nwkeffect}$	Relative network effect	0.295 *	Moderate network effects		
$U^{horizon}$	Decision horizon (users)	0.08 *	Two years		
$C^{synlevel}$	Synergy level	0.3 *	Moderate ease of multi-homing		
$C^{horizon}$	Decision horizon (complementors)	0.04 *	One year		
$P^{qualdiff}$	Variation in platform quality	0.678 *	Medium quality differences		
$P^{timediff}$	Entry timing difference	0.5	Successive market entry		
Simulation runs					
Design points:	1	Total runs:		1,500	
Repetitions:	1,500	Total runtime:		00h:15m:23s	

* Denotes empirically calibrated parameter values

In the present case of successive market entry, the market state at the end of the simulation can be either an oligopoly (OLI), a first-degree lock-in (LCK1) or a second-degree lock-in (LCK2). The first two states are well known from the previous experiments. A second-degree lock-in describes the dominance of a single technology that is suboptimal *in retrospect* because better alternatives have since become available (LCK2). This state occurs when the market locks in to one of the early entrants B to E so that the best platform A cannot prevail. Figure 8-24 presents the aggregate results of 1,500 runs.

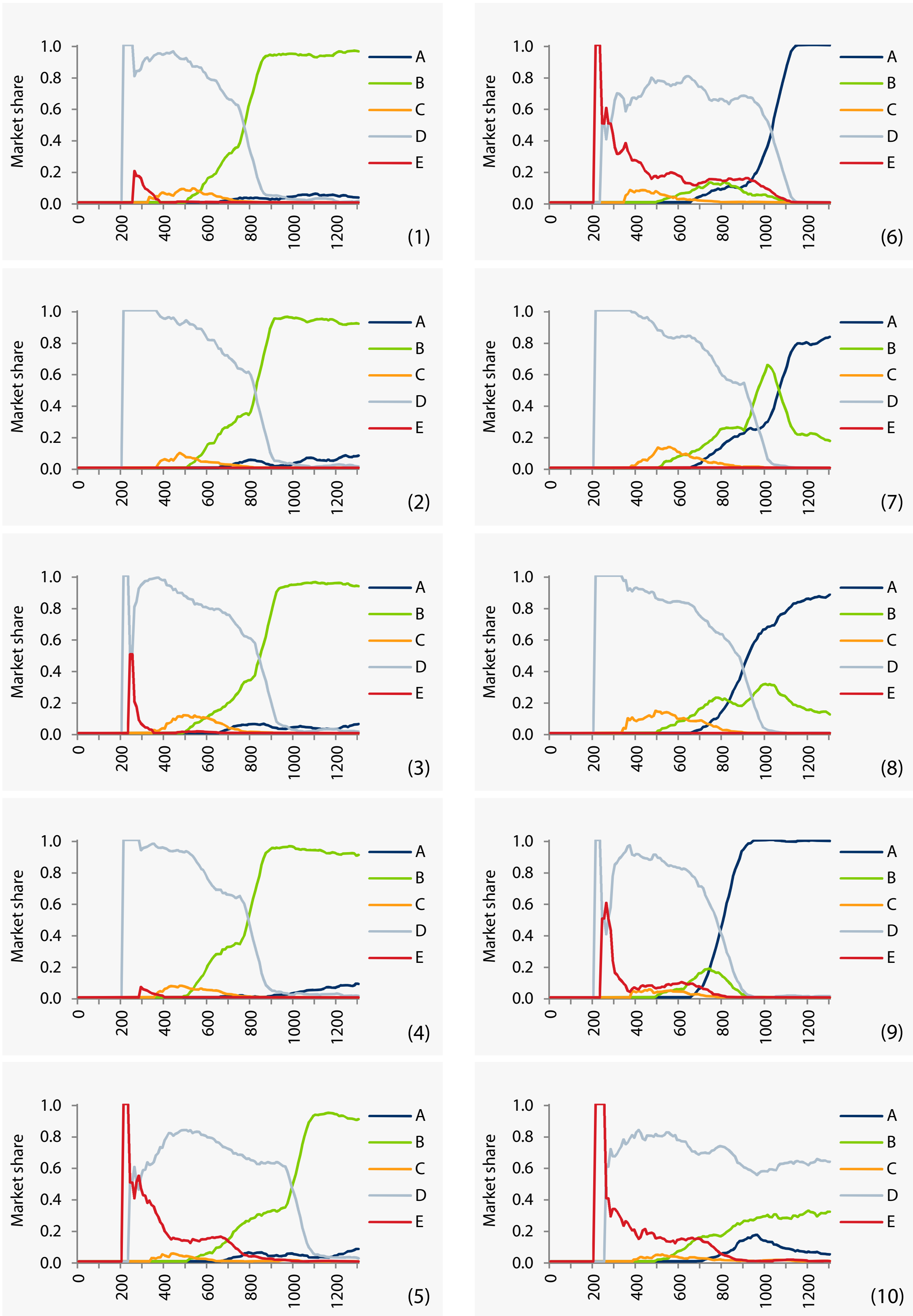
Figure 8-24 **Full calibration experiment with successive market entry**
Aggregate results of 1,500 runs



Starting from the same initial conditions, there is a huge variety of market outcomes. This again highlights the contingency inherent in the model. The market locks in to one of the inferior early entrants (LCK2) with a probability of 55 percent. As can be seen in the right figure, this is most often the second-best platform B. The best platform A manages to overcome the installed-base advantage of incumbents and achieve market dominance in 28 percent of cases (LCK1). Lastly, several platforms share the market in 17 percent of all runs (OLI).

The analysis of a number of illustrative simulation runs (see Figure 8-25) facilitates a better understanding of the aggregate results.

Figure 8-25 **Full calibration experiment with successive market entry: market share dynamics**
Different market outcomes starting from the same initial conditions;
runs 1-5: dominance of an inferior early-entrant (LCK2);
runs 6-9: dominance of the best technology platform (LCK1);
run 10: no lock-in, coexistence of several platforms (OLI)



The common result in all runs is that platform D, which enters the market rather early at t=163, dominates the market for a long period of time. In runs 1 to 5, it is later defeated by platform B, which is superior to D but still inferior to platform A (LCK2). In runs 6 to 9, the best platform A ultimately manages to achieve market dominance despite its late entry at time t=650 (LCK1). In run 10, several platforms coexist and no lock-in occurs (OLI).

The experiment shows that second-degree lock-ins are a frequent phenomenon. Superior technologies may not prevail because incumbents are able to defend their market leadership despite technological inferiority. In fact, according to the data, these second-degree lock-ins are the most probable market outcome. As such, order-of-entry effects seem to play a major role. However, the underlying causes for these suboptimal allocations need more consideration. In the case of successive market entry, what are the critical factors of influence that favor or hinder the probability of a second-degree lock-in? In the following, I address this question by means of another variation experiment.

8.10 Experiment 5: Strength of network effects and differences in platform quality in the case of successive market entry

This final experiment explores the impact of the strength of indirect network effects as well as the effect of quality differences in the case of successive market entry of the competing platforms. These two parameters are selected among the other independent variables because they have proved to be highly influential in the case of simultaneous market entry (see experiment 1). Table 8-11 summarizes the setup of the simulation experiment.

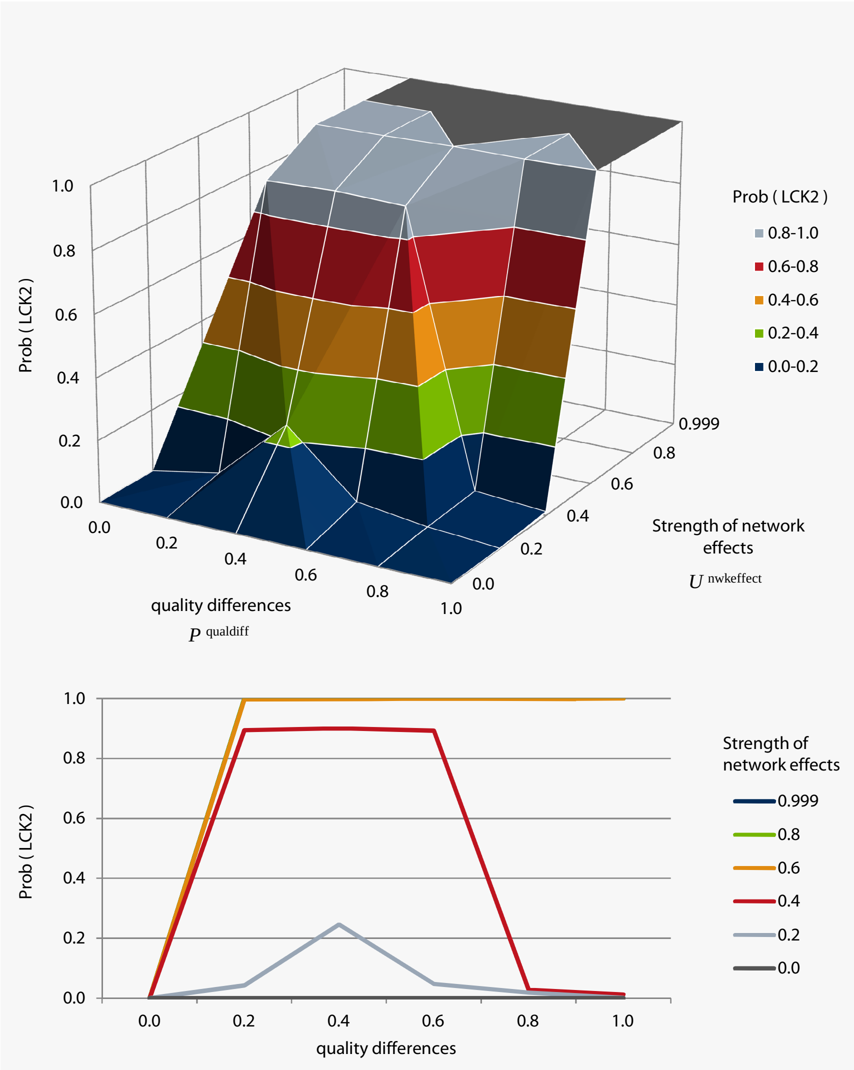
Table 8-11 Experiment 5 setup

Factors		*Min*	*Max*	*Step*	*Factor levels*
$U^{nwkeffect}$	Relative network effect	0.0	1.0	0.2	6
$P^{qualdiff}$	Variation in platform quality	0.0	1.0	0.2	6
Constant variables		*Value*	*Description*		
$U^{infolevel}$	Information level	0.37 *	Imperfect information		
$U^{ratiolevel}$	Rationality level	0.7 *	Bounded rationality		
$U^{horizon}$	Decision horizon (users)	0.08 *	Two years		
$C^{synlevel}$	Synergy level	0.3 *	Moderate ease of multi-homing		
$C^{horizon}$	Decision horizon (complementors)	0.04 *	One year		
$P^{timediff}$	Entry timing difference	0.5	Successive market entry		
Simulation runs					
Design points:	36	Total runs:		54,000	
Repetitions:	1,500	Total runtime:		07h:50m:13s	

* Denotes empirically calibrated parameter values

The experiment focuses on whether the market locks in to inferior early entrants. Thus, the probability for a second-degree lock-in serves as the dependent variable. Figure 8-26 presents the aggregate results of 54,000 simulations runs.

Figure 8-26 **Experiment 5: probability for a second-degree lock-in**
Effects of the strength of network effects and platform quality differences in the case of successive market entry; aggregate results of 54,000 runs

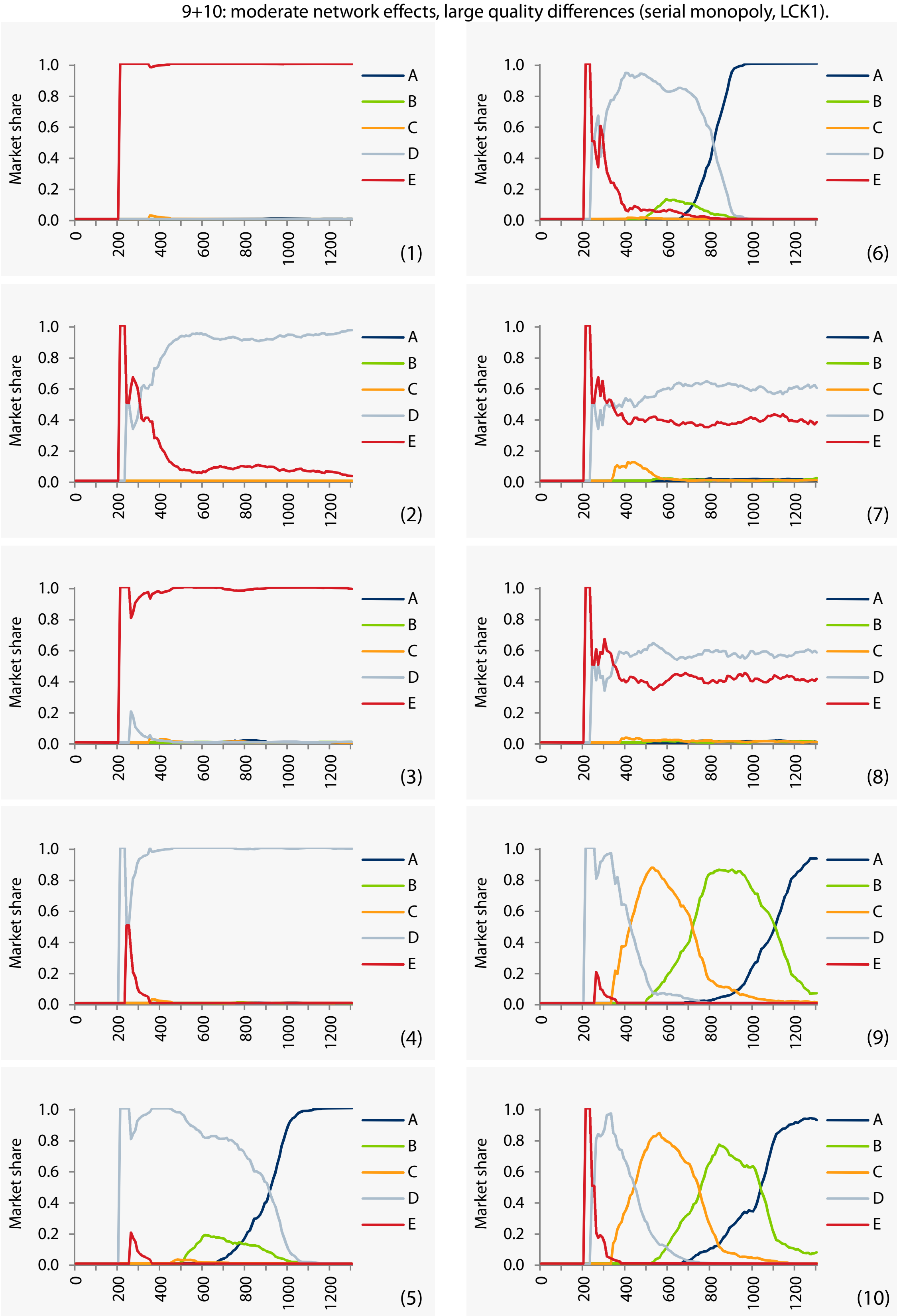


It is apparent from the data that strong network effects ($U^{\text{nwkeffect}} \geq 0.6$) drastically increase the probability for second-degree lock-ins. In this setting, superior technology platforms that enter the market at a later point in time cannot prevail against incumbent platforms. Under strong indirect network effects, the incumbent's installed-base advantage outweighs the technological advantage of late entrants.

In the case of medium network effects ($0.2 \leq U^{\text{nwkeffect}} \leq 0.4$), the market outcome highly depends on the level of quality differences between the platforms. The greater the improvement in quality, the more likely a superior late entrant can challenge the incumbent platforms. These results confirm recent findings by Zhu & Iansiti (2012).

In order to elucidate the aggregate results of the model, I show the competitive dynamics of individual simulation runs in the case of successive market entry below. Five scenarios with different levels of indirect network effects and quality differences are explored.

Figure 8-27 **Experiment 5: market share dynamics**
Runs 1+2: strong network effects, large quality diff. (LCK2); runs 3+4: medium network effects, small quality differences (LCK2); runs 5+6: medium network effects, large quality differences (LCK1); runs 7+8: moderate network effects, small quality differences (OLI); runs 9+10: moderate network effects, large quality differences (serial monopoly, LCK1).



Runs 1 and 2 demonstrate the model behavior in the case of strong network effects ($U^{nwkeffect}$ = 0.8) and large quality differences ($P^{qualdiff}$ = 1.0). As a result of the strong network effects, the market quickly locks in to the first mover (platform E, run 1) or second mover (platform D, run 2). Even though the technological advantage of new entrants is huge, they cannot prevail against the incumbent technology platforms which reap the benefits of their early installed base. Similar situations appear in runs 3 and 4 with medium network effects ($U^{nwkeffect}$ = 0.4) and small quality differences ($P^{qualdiff}$ = 0.2). Late entrants are 'not sufficiently better' to outweigh the indirect network effects that benefit the incumbent technologies. In all cases, a second-degree lock-in occurs.

The competition dynamics change in the case of medium network effects ($U^{nwkeffect}$ = 0.4) and large quality differences ($P^{qualdiff}$ = 1.0), represented by runs 5 and 6. At first, the market again locks in to platform D. Platforms C and B successively enter the market, but their technological superiority is not sufficient to seriously challenge the market leader. However, platform A manages to take over the market due to its clear superiority over all other platforms. Ultimately, the market is dominated by the best platform A.

Runs 7 and 8 present the case of moderate network effects ($U^{nwkeffect}$ = 0.4) and small differences in platform quality ($P^{qualdiff}$ = 0.2). Platforms E and D share the market right from the start and can defend their position against new entrants with only minor quality advantages. None of the platforms achieves a clear market leadership in the long-run.

Runs 9 and 10 are of special interest. In case of moderate network effects ($U^{nwkeffect}$ = 0.2) and large quality differences ($P^{qualdiff}$ = 1.0), the market dynamics take the form of "serial monopolies" (Liebowitz & Margolis 2001, p. 10). Each technology platform dominates the market for a period of time, before it is superseded by a superior successor. Ultimately, the best platform A wins the competition.

In summary, the simulation experiment has shown that in the case of successive market entry, both the strength of network effects and the difference in platform quality are important factors of influence. The stronger the indirect network effects and the smaller the advantages in platform quality, the more likely a suboptimal second-degree lock-in. If the indirect network effects are not excessively strong, distinct improvements in quality can always break existing lock-ins to inferior technology platforms.

This concludes the presentation of the simulation experiments. Before discussing the theoretical implications for path dependence theory as well as the practical implications for the smartphone industry, a robustness check is conducted to enhance the internal validity of the simulation results.

8.11 Robustness check

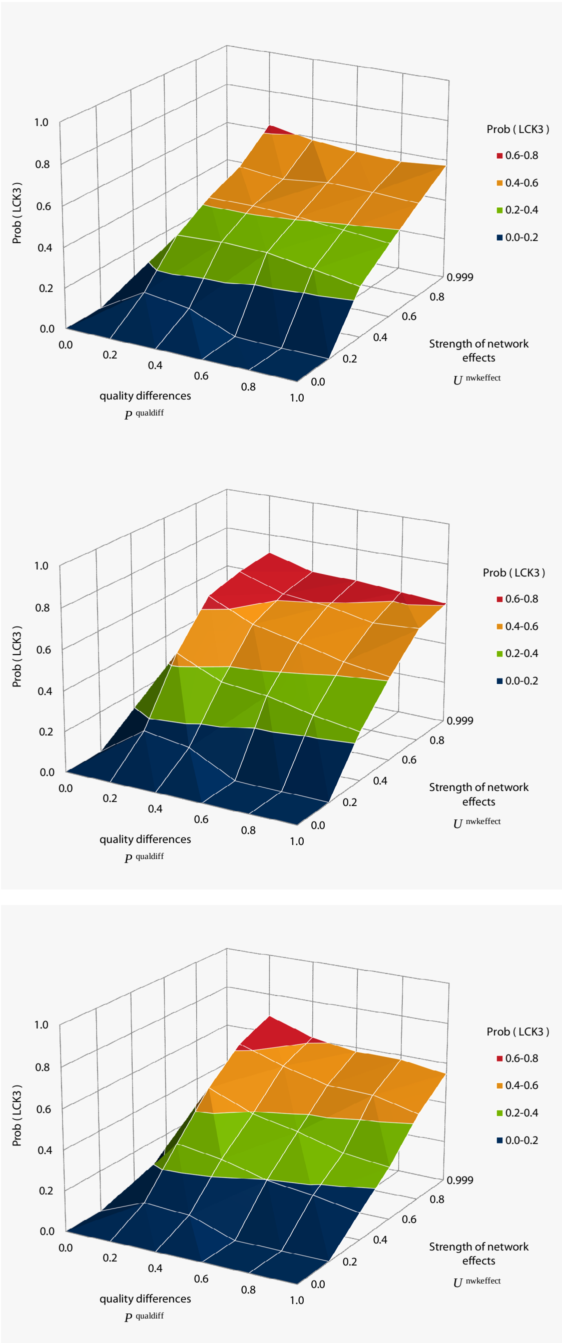
The robustness check serves to increase confidence that the identified causal relationships are stable (Harrison et al. 2007). For that reason, sensitivity analyses are conducted to assess whether the behavior of the system is sensitive to changes in model parameters *beyond* the experimental factors (Robinson 2004). As such, the robustness check addresses the fundamental question of whether the simulation results still hold if the computational representation of the model is changed (Davis et al. 2007).

First, it has to be decided which model parameters to subject to a sensitivity analysis. In total, the model has 19 parameters, which have been divided into eight independent variables and 11 control variables (see Table 8-1). The influence of the independent variables has already been analyzed in depth by the various variation experiments. Nine of the 11 control variables have been calibrated on the basis of empirical evidence from the smartphone industry, which served to deliberately restrict the degrees of freedom of the model. Obviously, different values for these empirically calibrated parameters may result in different model outcomes, for instance due to a change in the speed of diffusion, or a different network topology. However, these potential effects are not the focus of the research question. Accordingly, the robustness check focuses on the two remaining model parameters which have been set rather arbitrarily: the number of user agents and the number of complementor agents. To examine their effects, the robustness check concentrates on experiment 1 as it constitutes the starting point for all other experiments.

Number of user agents

It has been argued that the number of agents is limited by the performance constraints of the computer hardware. For that reason, the number of user agents was set to U = 500. For the purpose of the robustness check, this default value is adjusted both upward and downward. Experiment 1 is repeated with 250 agents and 2,500 user agents. Figure 8-28 compares the aggregate results in the case of 250, 500 and 2,500 user agents.

Figure 8-28 **Robustness check: influence of the number of user agents**
Results of experiment 1 with 250, 500 and 2,500 user agents (from top to bottom)



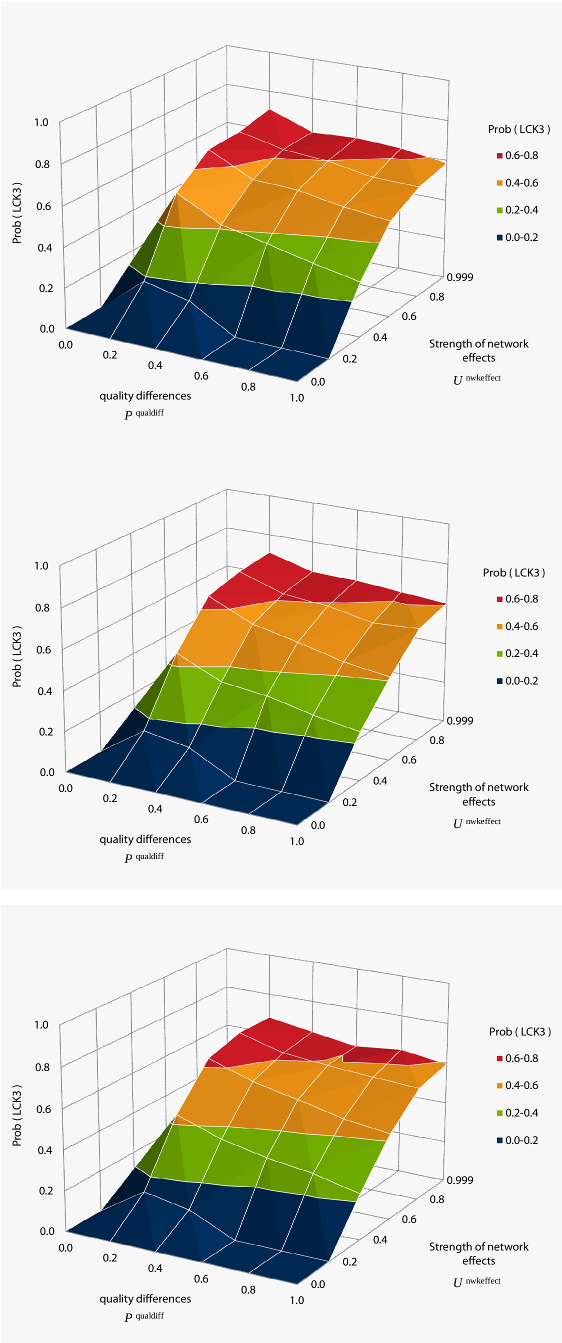
It can be seen that a change in the number of user agents has only a minor impact on the model behavior. The influence of the strength of network effects and the difference in platform quality on the probability of a third-degree lock-in remains largely unaffected. Small differences in the absolute effect size can be attributed to slightly different diffusion patterns, which affect the initial time of adoption of the user agents. In total, a change in the number of user agents has a negligible impact on the model behavior.

Number of complementor agents

Following the same principle, the number of complementor agents is subjected to a sensitivity analysis. For the purpose of the robustness check, the default value of $C = 50$ is adjusted both upward and downward.[157] Figure 8-29 compares the aggregate results in the case of 25, 50 and 250 complementor agents.

157 Please note that, ceteris paribus, a change in the number of complementor agents would alter the number of complementary products that are developed in a given period of time: fewer complementors produce fewer complementary products. As a result, the empirically calibrated strength of indirect network effects would be affected. To control for this undesired effect in the robustness check, the 'upscaling' of complementors' output is adapted to still match the empirical findings. Please refer to section 7.5.4 for more details.

Figure 8-29 **Robustness check: influence of the number of complementor agents**
Results of experiment 1 with 25, 50 and 250 complementor agents (from top to bottom)



It is apparent from the data that the number of complementor agents has almost no effect at all. The influence of the strength of network effects and the difference in platform quality on the probability of a third-degree lock-in remains unchanged.

To conclude, the objective of the robustness check was to examine the impact of arbitrarily chosen control variables. It has been shown that the model behavior is unaffected by the number of agents. The analyses for experiment 1 gave all reason to believe that this insensitivity also holds for the other experiments. As a result, the identified causal relationships in the model can be considered robust.

9 Discussion

This final chapter is devoted to the discussion and interpretation of the simulation results. First, their validity is discussed in order to critically evaluate the findings. I then draw attention to the theoretical implications for path dependence theory and outline the practical implications of the work. Furthermore, I address limitations of the study and recommend avenues for further research. I conclude by summarizing the contribution of this dissertation.

9.1 Validity of the findings

Four measures are commonly used in the social sciences to assess the conceptual and methodological quality of research: (1) construct validity, (2) reliability, (3) internal validity and (4) external validity (Hoyle et al. 2001; de Vaus 2003).[158]

Construct validity refers to whether the measures in a research project actually capture the theoretical concepts that they are supposed to investigate. In general, construct validity is a particular strength of simulation research, as "simulation requires precise specification of constructs and their measures, and so avoids 'noisy' measurement that affects construct validity in empirical research" (David et al. 2007, p. 490). In particular, the present study has taken great care to ensure that all concepts included in the model, such as network effects, contingency, lock-in etc., are precisely defined (chapter 2) and formally described (chapter 5). Furthermore, the computational representation of the theoretical constructs is fully disclosed in the model source code in 0. All of these actions ensure a high degree of construct validity.

Reliability concerns the extent to which the results of a study can be consistently reproduced. As highlighted in the design of experiments (section 8.2.4), the large, statistically derived number of repeated simulation runs ensured that the aggregate results reflect the 'true

158 In the context of simulation research, the terms *verification* and *validation* are frequently used (Gilbert & Troitzsch 2005) to address similar questions: Is the simulation implemented correctly (verification)? Is it a good representation of the target (validation)? Nevertheless, in order to enhance acceptance and understanding of simulation research in the scientific community, it is believed beneficial to rely on the four established criteria that are widely used in the social sciences. Content-wise, the different terms for assessing the quality of research have much in common: verification corresponds to internal validity, whereas validation (in simulation terms) corresponds to external validity (Gilbert & Troitzsch 2005, p. 23).

average behavior' of the stochastic model. As a consequence, repeating the simulation experiments reliably generates the same data within the given margin of error.

Internal validity relates to the capacity of a research design to clearly identify causal relationships among the variables (Campbell & Stanley 1966). For the present study, the computer-based simulation provided a controlled research setting for examining the causal links between the independent variables and the occurrence of technological lock-ins. Internal validity is a core strength of simulation research (Davis et al. 2007). The continuous verification process throughout the different stages of the research ensured that the identified effects are not caused by errors in the computational representation of the model.[159] In addition, the model behavior was explored for a range of well-known scenarios and was compared to existing theory by the use of a base case experiment. This experiment revealed that the simulation is able to replicate the properties of Arthur's seminal model of technological path dependence (Arthur 1989). These findings enhance confidence in the simulation and increase its internal validity (Davis et al. 2007). Lastly, the robustness check also confirmed the internal validity of the results.

External validity, or generalizability, refers to the domain to which findings can be generalized beyond the scope of the particular study (Campbell & Stanley 1966). In simulation research, external validity addresses the relationship between the simulation model and its real-world counterpart: Is the simulation a "good model of the target" (Gilbert & Troitzsch 2005, p. 23)? It has been argued that for agent-based models the empirical validation can take place at both the micro and macro level (Law 2007; Fagiolo et al. 2007; Garcia 2007). The extensive micro-level validation in chapter 7 ensured that the model assumptions regarding the agents' behavior and decision heuristics match those of the target system. In addition, the model parameters were calibrated on the basis of quantitative and qualitative empirical data.[160] This empirical calibration not only enhances the external validity of the results, but it also serves to restrict the degrees of freedom of the model.

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159 The various methods applied for verification are described in detail in the context of the phase model of simulation research in section 4.3, as well as in section 8.1.

160 Note that validation and calibration are two distinct steps. For instance, by means of qualitative research it was shown that the reach-maximizing decision heuristic for complementor agents in the simulation model approximates the decision behavior of application developers in the smartphone industry (*validation*). As a second step, the model parameters affecting complementors' platform choice were estimated based on empirical evidence (*calibration*).

Ultimately, in order to further increase the external validity of the simulation, the simulation output needs to be compared with empirical data collected from the real-world target (Gilbert & Troitzsch 2005). In this regard, empirical validation at the macro level refers to the "procedure through which the modeler assesses the extent to which the model's outputs approximate reality" (Fagiolo et al. 2007, p. 191). However, comparing the model behavior with the real-world target is problematic for several reasons. First, the emerging smartphone industry, for which the generic model has been calibrated, is a 'phenomenon in the making' — hence, the final outcome in this market cannot yet be observed. Second, whenever a target process and its model are subject to random influences, an "exact correspondence" is unlikely (Gilbert & Troitzsch 2005, p. 23). Instead, the distribution of the simulation results would need to be compared against an empirical distribution of outcomes.[161] For the present simulation study, this approach is impractical. It is assumed that the target (platform competition in the global smartphone industry, and similar cases) is a nonergodic process with multiple theoretically possible outcomes. Given that the target process occurs only *once* in reality for a set of initial conditions, it is impossible to obtain an empirical *distribution* of outcomes to compare it with a simulated distribution.[162] Therefore, empirical validation by means of a strict output comparison with the target is unfeasible for the proposed simulation model of path-dependent competition processes in two-sided markets.

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161 For example, assume that we create a perfectly realistic simulation model of a six-sided die. Rolling the (physical) die and running the simulation (i.e., 'rolling' the virtual die) is likely to yield different results for a single trial. However, comparing the empirical distribution of 1,000 trials with the simulated distribution of 1,000 simulation runs will show very similar results. This provides confidence that the simulation model is valid.

162 Due to the contingent nature of path-dependent processes, even a perfect model of platform competition would most likely not resemble a specific empirical trajectory. Just as in the die-rolling example, there is no correspondence between a single empirical case and a single simulation run — even with a perfect model. However, in contrast to the example, it is impossible to create a distribution of empirical outcomes because each empirical case is unique. Hence, validating the model by means of comparing an empirical distribution with a simulated distribution of outcomes is impossible. Nevertheless, what *can* be determined is whether a specific empirical outcome is included in the set of simulated outcomes (though this is only a subset of the solution space of the stochastic model). If the specific empirical outcome cannot be approximated by the simulation in at least one of the repeated runs, the model is most likely not a valid representation of the empirical target.

Davis et al. argue that external validity is the primary weakness of simulation research, and that especially overly simplistic and empirically distant models “fail to capture critical aspects of reality” (Davis et al. 2007, p. 496). The present study addresses this criticism by incorporating a detailed representation of path-dependent technology competition which exceeds the reality level of other existing models. Given the extensive micro-validation and empirical calibration of the proposed model for the smartphone industry, external validity can be claimed at least to some extent for this particular market. For other applications of the model, further validation procedures are required to assess the external validity. For instance, Gilbert proposes that these types of “middle range” market models should “be satisfied with qualitative resemblances” of the observed dynamics (Gilbert 2008, p. 42).

Nonetheless, it must be stressed that the proposed simulation model has not been designed for predicting empirical phenomena. It aims to refine the theory of technological path dependence by unveiling as yet undiscovered implications derived from the axioms of the theory. In this regard, the simulation model contributes to the “exploration, elaboration, and extension” (Davis et al. 2007, p. 482) of path dependence theory. Qualitative case studies and simulation experiments have much in common, given that “case studies, like experiments, are generalizable to theoretical propositions and not to populations or universes” (Flyvbjerg 2006, p. 224; see also Yin 2009). The simulation model proposes new theoretical relationships in the context of technological path dependence — without establishing “how much of the world works this way” (David 1985, p. 332). In order to enhance the scope of the findings beyond the artificial world of the simulation, the derived relationships need to be validated by further qualitative and quantitative empirical research. In conclusion, the proposed model provides a valuable thinking tool for reflecting on the conditions for technological lock-ins in platform markets. However, the findings of the simulation study should not be generalized without additional empirical support.

These words of caution on the external validity of the results set the scene for a discussion of the theoretical and practical implications of the findings. I first elaborate on the implications for path dependence theory, before addressing the practical implications of the study. In the subsequent section, some avenues for further research are suggested. I conclude by highlighting the overall significance and contribution of the dissertation.

9.2 Implications for path dependence theory

The simulation experiments were able to identify conditions favorable to the emergence of technological lock-ins in two-sided markets and thereby provide profound implications for path dependence theory. The results indicate that path-dependent processes, and in particular technology competition in network markets, are to a high degree determined by random influences. This emphasizes the influential role of contingency for the outcome of market processes and supports the argument by David that "market structures in some areas of the economy — especially those where network externalities and bandwagon dynamics are especially important — are particularly susceptible to the shaping influence of specific historical [random] events in the evolution of the industries concerned" (David 2007, p. 104).

This finding is rather sobering on the one hand, because it highlights that no predictions can be made for individual cases of technology competition. Even with the insights gained from the present simulation study, no definite statements can be made ex-ante on whether or not the market will end up in an inferior technological lock-in, given the contingent nature of these processes. On the other hand, however, the findings enable us to draw valuable conclusions in terms of probability. On the basis of the initial conditions of the process and the causal relationships which were identified by this research, the probability for an inferior technological lock-in can be estimated. This corroborates the argument of Vergne and Durand (2010), who suggest that "simulations can help assess the probability of path dependence" (Vergne & Durand 2010, p. 750).

In line with other research on technological path dependence, the notion of lock-in has been conceptualized as standardization on a single technology. However, technological standardization alone is of little interest to path dependence scholars. For instance, it is intuitively understood why society follows a single keyboard layout instead of a variety of different keyboards. The different self-reinforcing mechanisms discussed in the context of technological path dependence provide valuable theoretical underpinnings for this empirical observation. The more interesting question is why society, by means of market-based decentralized decision-making, has chosen the inferior QWERTY standard. To account for the difference between 'standardization' and 'standardization on the wrong standard', three distinct degrees of lock-in were proposed based on well-established efficiency considerations.

Third-degree lock-ins are of particular interest for path dependence theory because they constitute a *remediable* inferior market outcome, which is thus inefficient. The simulation model found that third-degree lock-ins are a rare event. Far from being the rule, suboptimal market outcomes are the exception for most parameter settings. This is consistent with the empirical evidence showing that despite the existence of many network markets, only few prominent cases of inferior lock-ins have been observed. In line with the existing theory, it has been shown that third-degree lock-ins arise under the conditions that (1) an inferior technology platform gains an initial lead in adoption, and that (2) positive feedback reinforces this initial lead, so that the market ultimately tips to the inferior technology platform. These two conditions were explored in depth by means of the simulation model. It showed that imperfect information and bounded rationality are held responsible for the contingent lead in adoption of an inferior platform. This argument will be discussed later in more detail with regard to the notion of 'small events'. Positive feedback in the form of indirect network effects results from the interdependent actions of users and complementors in two-sided markets.

For first- and second-degree lock-ins, strong network effects are sufficient for their occurrence, even in the limiting case of complete information and perfect rationality. Second-degree lock-ins, which can only arise in the case of successive market entry, are similar to third-degree lock-ins in that they denote suboptimal market outcomes. However, second-degree lock-ins should not be prejudged as inefficient. Such a claim would need to weigh the collective benefits of the superior technology against the collective switching costs, which are outside the scope of the model. Hence, without further empirical analysis, a second-degree lock-in may or may not be a third-degree lock-in.

First-degree lock-ins denote standardization on the best available technology platform, which is by no means inefficient. Nevertheless, such markets may lose the capability to adopt superior alternatives that become available at a later point in time. Therefore, first-degree lock-ins must be regarded as "potentially inefficient" (Sydow et al. 2009; Schreyögg & Sydow 2011), a term which was first brought up in the context of organizational path dependence.

In the following, I discuss the theoretical implications derived from the different simulation experiments, each of which addressed particular factors of influence.

Strength of network effects and differences in platform quality

Experiment 1 explored the impact of the strength of the indirect network effects as well as the effect of quality differences between the competing platforms. It showed that the higher the strength of network effects and the smaller the differences in quality, the more likely a third-degree lock-in becomes. The strength of indirect network effects in the proposed simulation model directly corresponds to the magnitude of increasing returns in Arthur's seminal model (1989). In line with Arthur's model, I showed that the strength of indirect network effects is highly predictive of the probability of lock-in (Arthur 1989). Moreover, based on the strength of network effects and the level of quality differences, the model is able to *quantify* the probability for inferior market outcomes.

David proposes characterizing path-dependent processes by their "degree of historicity" (David 1997, p. 27) in order to describe the extent to which single historical events determine the outcome of the process. The present study follows this call to measure the magnitude of self-reinforcement, which can be thought of as the strength of the influence of the past. I was able to show that stronger network effects significantly increase the degree of historicity. The most extreme setting serves to underline this finding: in the case of very strong network effects ($U^{nwkeffect} = 0.999$), the contingent decision of the first agent is the single 'small event' that completely determines the unfolding process. In this regard, simulation research provides a unique opportunity to explore the impact of single events for different degrees of historicity.

Regarding the relationship between quality differences and the probability for third-degree lock-ins, the results highlight the intuitively convincing finding that such lock-ins become more likely when the differences between the technological alternatives are small. However, due to the marginal level of inferiority this misallocation does not result in major efficiency losses. Hence, smaller quality differences increase the probability of inferior lock-ins, but at the same time decrease the 'severity of lock-in'. Thus, when exploring inferior lock-ins, scholars of technological path dependence should always account for the level of discrepancy between the prevailing standard and the optimal (hypothetical) market outcome: the higher the foregone efficiency gains, the more convincing the argument for path dependence and lock-in.

Imperfect information and bounded rationality

Experiment 2 investigated the effect of imperfect information and bounded rationality. By taking a gradual perspective of these cognitive limitations, the simulation model allows to quantify the impact of more or less rationality among agents. The simulation model revealed that both limitations of knowledge and limitations of rationality can lead to wrong platform choices. Due to imperfect information, individual agents may not be informed about the optimal technology. And, even if they consider it in their platform choice, their boundedly-rational behavior may prevent them from recognizing its superiority. Particularly in the early stage of the diffusion processes, the resulting suboptimal decisions of individual agents are reinforced by indirect network effects and can therefore trigger inefficient lock-ins to inferior technology platforms.

The analysis of the role of bounded rationality and imperfect information provide new insights into the nature of 'small events'. The simulation model allows to identify the seemingly insignificant decisions which triggered bifurcation, ultimately leading to the dominance of an inferior technology. The model showed that the initial lead of an inferior platform results from a *chain* of unfortunate circumstances. Referring to the above discussion on the degree of historicity, the model revealed that for most parameter settings it is not a single event, but rather an accumulation of independent events that determines the path-dependent process. Self-reinforcement does not occur instantly. Thus, several agents need to independently choose a particular inferior technology in order to create enough momentum to direct the self-reinforcing network effects to the wrong platform. This finding supports the argument by Arthur that "it [the market outcome] depends on the cumulation of random events" (Arthur 1989, p. 124). For further research on technological path dependence, this raises doubt on the feasibility of tracing back the chain of random events in a decentralized market by the use of retrospective empirical analysis. This again highlights the benefits of simulation models for path dependence research.

Switching

Experiment 3 examined the role of the decision horizon, which determines how often agents reconsider their former decisions and switch to alternative technology platforms. The decision horizon serves as a proxy for any form of individual inflexibilities, such as learning effects or platform-specific assets, which may delay the move to a superior alternative. It was shown that the decision horizon, except for extremely short time periods, does not play a significant role in the emergence of technological path dependence. These findings indicate that individual inflexibilities are not the cause of technological lock-ins in network markets. They may explain why individual agents stick to their initial technology choice, but they cannot account for why a whole market economy, consisting of independent decision-makers, collectively follows an inefficient path. This suggests that research on technological path dependence should focus less on inertial forces at the individual level, such as learning effects. Instead, it should focus more on inter-agent positive feedback mechanisms that give rise to macro-level inflexibilities, such as complementarities and network effects.

In addition, the simulation has provided further insights into the temporal occurrence of third-degree lock-ins. It is only in the very first phase of the diffusion process that individual decisions may have long-run consequences. Thus, inefficient lock-ins occur, if at all, at a very early stage. This highlights the critical influence of early adopters on the outcome of path-dependent technology competitions. Accordingly, this suggests that path dependence scholars should concentrate their research effort on the very early stage of the process under review. History is the key for understanding lock-in phenomena. This supports the call by David (2007) that empirically oriented researchers should rely heavily on the tools of historians to uncover the very origin of path-dependent processes.

Multi-homing

Experiment 4 focused on the impact of multi-homing on the probability of technological lock-ins. The existing research on technological path dependence has so far ignored the effect of multi-homing strategies. In particular the theoretical contributions have focused on the choice between one of two alternatives, thereby neglecting that agents often can support several competing technology platforms. The proposed simulation model fills this gap and introduces the notion of multi-homing, which originates from the theory of two-sided markets, to the path dependence literature.

The simulation model has shown that higher synergy levels, which represent a greater degree of compatibility between the technology platforms, encourage complementors to pursue multi-homing strategies. The analysis revealed that it is not only individually beneficial for complementors to hedge their bets by following a multi-homing strategy; it also sharply reduces the probability for suboptimal market outcomes. The market-driven selection process remains open for a longer period of time and alternative technologies do not get locked-out as easily. Hence, the market is less affected by the initial decisions of individual actors and is thus more likely to select the optimal technology. Katz and Shapiro highlight that “the uncertainties of technological progress suggest another benefit to variety: standardizing on a single system can be very costly if the system selected turns out to be inferior to another system” (Katz & Shapiro

1994, p. 106). The results of the present study provide evidence that multi-homing strategies indeed provide an opportunity to minimize ex-ante the risk of inferior technological paths. The bifurcation point, at which the market tips towards a single technology, is postponed and the decision-making phase regarding the prospective standard is extended (Ackermann 2001, p. 42). Therefore, multi-homing represents a way to "counteract the 'excess momentum' of bandwagon movements in network product and service markets that can prematurely commit the future inextricably to a particular technical standard before enough information has been obtained about the likely technological … implications of an early precedent setting decision" (David 2007, p. 110). The ease of multi-homing is not only affected by technological factors but also by the legal framework, which is regulated by policy makers. This issue will be addressed in more detail in the upcoming section on the practical implications of the study.

Successive market entry

Experiment 5 explored the model behavior in the case of technological progress. In this experiment, superior technology platforms successively entered the market and challenged the incumbent platforms. In this setting, both the strength of network effects and the difference in platform quality emerged as important factors of influence that determined the market outcome. The simulation model proved able to represent a variety of realistic market scenarios. In general, it revealed that the stronger the indirect network effects and the smaller the advantages in platform quality, the more likely a suboptimal second-degree lock-in becomes. This corresponds to the findings in the case of simultaneous market entry (experiment 1).

The notion of second-degree lock-ins to early entrants emphasizes that the literature on first-mover advantages and the literature on technological path dependence have much in common (Tellis et al. 2009; Schilling 2002; Mueller 1997). Both address the same phenomena from different perspectives: the strategy and marketing literature takes a micro perspective and focuses on the business implications for incumbents and/or new entrants; in contrast, the path dependence literature adopts a macro perspective and discusses technological lock-ins with regard to market efficiency. Therefore, it is believed that both disciplines can benefit from a closer integration of the related streams of literature. Nevertheless, some scholars contest the connection between first-mover advantages and path dependence. Vergne and Durand argue that "a persisting market domination explained by first mover advantage would not qualify for a path dependence explanation" because "a first mover advantage is rarely contingent" (Vergne &

Durand 2010, p. 741).[163] The results from the simulation study reject this argumentation, most notably on the basis of the different market outcomes in the full calibration experiment in the case of successive market entry (section 8.9). It was shown that, despite differences in entry timing between the competing platforms, the process remained contingent and was not completely determined by its initial conditions, i.e., the order of entry. As a result, even lock-ins resulting from a first-mover advantage qualify for a path dependence explanation, provided that it can be shown, or convincingly claimed, that other market outcomes would have been possible. In this regard, computer-based simulation or counterfactual investigation (Durand & Vaara 2009) is the research method of choice.

The simulation findings suggest that, instead of a strict first-mover advantage, an early-mover advantage exists in network markets. In most instances, incumbent platforms benefited from their existing installed base and retained market leadership despite their technological inferiority. In these circumstances, late entrants had little chance to successfully enter the market, even when providing a superior product. Translated to the path dependence context, the market dominance of early movers refers to a second-degree lock-in. However, the model also showed that in most settings *substantial* improvements in quality are able to break existing lock-ins to inferior technology platforms. The study exemplified that the stability of a lock-in can be measured by the magnitude of the external shock that is required to overcome the state of inflexibility. In the model, external shocks were represented by the successive entry of superior technology platforms, with the magnitude of these shocks being equal to the level of quality improvements, i.e., the extent of technological progress. This revealed that the simulation methodology can be fruitfully applied to test the stability of lock-ins, and may also serve to explore the avenues of path-breaking change.

163 Adopting a narrow understanding of path dependence, both contingency and self-reinforcement have been defined as necessary conditions that distinguish path dependence from other related concepts (see section 2.1.5).

9.3 Practical implications

It has already been stressed that the proposed simulation model is not intended to predict the outcome of the ongoing platform competition in the smartphone industry.[164] In particular, two factors limit the predictive power of the model for the empirical case. First, neither the quality nor the entry timing of the competing platforms, such as the *Apple iPhone* and *Google Android*, were calibrated empirically. Second, the model deliberately abstracts from platform differentiation and market segmentation by assuming homogeneous preferences.[165] Despite these abstractions, the findings of the simulation study are believed to have profound practical implications for the smartphone industry and, more generally, for other cases of platform competition in two-sided markets. Therefore, the present section is devoted to transferring the model results into practice and briefly discussing the levers for business strategy.

The simulation experiments have shown that the relative strength of indirect network effects has the largest impact on the probability for lock-in in two-sided markets. Against this background, the well-known lock-in to *Microsoft Windows* in the PC industry is not surprising. While an empirical calibration of the parameters to the PC industry was outside the scope of this study, it can be assumed that network effects are much stronger compared to the smartphone industry because the technological platform itself, i.e., the PC operating system, is largely useless without compatible software applications (Dobusch 2008; Shapiro & Varian 1999).[166] In contrast, the relative strength of network effects is less strong for smartphones due to the fact that, without installing a single app, users can derive value from making phone calls, surfing the internet or using the built-in camera. Thus, the substantial inherent value of any platform indicates that there is less pressure for market concentration in the smartphone industry, thereby reducing the risk for (inferior) lock-ins.

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164 The relationship between the simulation model and the empirical case was discussed in section 9.1 regarding the external validity of the findings.

165 Relaxing this assumption would greatly complicate the discussion of market efficiency, which is at the heart of this model on technological path dependence. This will be discussed in more detail in section 9.3 regarding the limitations of the study and further avenues for research.

166 This was even more the case before the rise of the internet which made functionality available in the form of cross-platform web applications via the browser.

More generally, experiment 5 (see section 8.10) explored in-depth the market dynamics for different levels of network effects and quality differences in the case of successive market entry. The results provide profound practical implications by highlighting the determinants of platform competition in two-sided markets. For instance, the findings allow us to draw conclusions on the probability of success for late entrants.

The discussion follows the different scenarios illustrated in Figure 8-27. In the case of strong relative network effects (runs 1-4), the market is likely to be permanently dominated by one of the early entrants. Late entering platforms cannot prevail against the incumbent platform. Although they provide a technically superior product, the advance in technological progress does not outweigh the existing network effect. Transferred to the QWERTY case, this result resembles the position of Liebowitz & Margolis (1990), who emphasize that QWERTY enjoyed a 60-year head start and argue that late-entrant Dvorak was simply not superior enough to make a difference.

In the case of medium strength network effects and distinct technological progress (runs 5 & 6), early entrants enjoy a period of market dominance. Some of the successor technologies struggle, but a later generation of technically improved platforms finally overtakes the market. In the long run, quality wins — thus, any form of market regulation is unnecessary. In this situation, a late entrant can compete successfully, provided that its technological advantage is more than marginal. Furthermore, this shows that an early market entry is not always beneficial. Assuming that the platform's quality cannot be incrementally increased while it is on the market, taking a later start may be the superior strategy. For instance, this could explain the fall of *Nokia* in the smartphone industry. Being the clear market leader since the very beginning, *Nokia* stuck to its technically inferior *Symbian* platform in order to not lose compatibility with the installed base of developers and apps. New entrants *Apple* and *Google* were able to enter the market with a fresh, superior platform without having to deal with backward compatibility issues, and rapidly took over market leadership. In such market settings, timing is critical and neither the first nor the last entrant is likely to compete successfully (Schilling 2002).

Lastly (runs 9 & 10), the market dynamics can also take the form of serial monopolies (Liebowitz & Margolis 2001). Each platform dominates the market for a limited period of time before it is superseded by a superior successor. In these circumstances, firms are advised to maximize short-term profits, as the decline of their platform is foreseeable.

For a successful market entry strategy, it should be noted that platform quality and complementary products for the platform are to some extent interchangeable. Users evaluate the technological platform and the portfolio of compatible products as a whole package. Even though compatible products are provided by independent firms, the platform provider is able to exert considerable influence on the supply. In this regard, platform providers are faced with a trade-off between investing additional resources in the technological development of the platform or incentivizing developers to increase the stream of complementary products. For instance, platform providers such as *Google* try to get application developers 'on board' their platform with complimentary devices, free training sessions and access to industry conferences as well as more favorable revenue sharing terms in their app stores. With this in mind, platform providers are advised to carefully evaluate the marginal benefit from investing an additional dollar in technology versus investing in their relationship with complementors.

Compatibility is a core issue in markets with indirect network effects. Therefore, experiment 4 was devoted to the impact of multi-homing strategies. The simulation supported the empirical findings by Corts & Lederman (2009) that the tendency towards market tipping decreases with higher synergy levels, corresponding to lower costs for cross-platform development.

With regard to the smartphone industry, the importance of this model parameter needs to be emphasized. In particular, two factors increase the level of synergies for multi-platform development: (1) the use of cross-platform development tools and abstraction layers, termed 'middleware', and (2) the technical capabilities of web applications that run across all platforms because they do not rely on native code. Our empirical research showed that developers are currently taking a critical look at these possibilities:

> "I don't necessarily believe in abstraction layer. … It impacts performance and I can't get to the parts of the platform that I really need to get to. … A lot of those abstraction layers that we tend to put on top of platforms end up not getting the developer adoption we would like to see."
>
> (Software engineer, large network operator, *OSIM World 2009*)

> "Middleware limits the functionality of applications to the lowest common denominator. It may be working out for simpler applications, but not for complex applications."
>
> (App developer, *OSIM World 2009*)

> "Native runtime is very important to do the really innovative stuff [applications]."
> (App developer, *Droidcon 2009*)

As such, most applications are currently written for one specific smartphone platform in native code. Nevertheless, developers are still seeking easier multi-platform development because it would allow them to sell their apps to a broader market. In contrast, smartphone platform providers tend to be skeptical because they consider platform-exclusive apps as an effective barrier to entry against new competitors:

> "Cross-platform is where we developers want to get, but the companies [the platform providers] want a lock-in — it's obvious! They want the most passionate developers exclusively on their platform to make the platform the most advanced one and the most sexy one. Well, that's not the way we think and I don't know if it will work out."
> (Developer, *WipJam@IT Profits 2010*)

The necessity for native apps that are specifically developed for a single platform is uncertain. Some industry experts see web applications as the common denominator that will accomplish full compatibility between all platforms in the future:

> "Again, I think one consistent thread across all of the platforms that we are talking about here, long term, is going to be the internet [i.e., web applications], and I do believe that this will be the equalizer across them."
> (App developer, *OSIM World 2009*)

As a consequence, platform compatibility and the possibility for multi-homing will have a crucial impact on the future market structure. Looking at the development of platforms' market shares in recent years (see Figure 6-7), the trend toward market concentration in the smartphone industry is undeniable. Some industry observers go so far as to expect a lock-in situation similar to the PC industry:

> "This is a typical network industry: you have increasing returns and lock-in — the winner takes it all!" [167]
> (CEO, medium-sized software company, *Droidcon 2010*)

[167] Note the terminology: apparently, (some) actors are quite knowledgeable about the dynamics and theoretical underpinnings of path dependence.

Other industry experts predict that no single platform will dominate the smartphone industry like *Microsoft* rules the PC industry, as they expect the market to be more fragmented, with two or three platforms remaining (Helft 2010). To conclude, the outcome of the fierce platform competition in the smartphone industry remains wide open.

9.4 Limitations and further research

This section is devoted to discussing limitations of the study and proposing avenues for further research. The limitations in terms of external validity of the simulation results have already been covered extensively in section 9.1. Thus, the focus here is on additional simulation experiments that could be conducted as well as potential additions to the model.

As described in the design of experiments, the parameter variation experiments covered a selection of model variables. Hence, only a subset of the 19-dimensional parameter space has been explored. Further simulation experiments with this model could investigate, for instance, the effect of the diffusion speed/pattern or the impact of the rate of innovation on the probability of lock-in. In addition, further interaction effects between the model variables could potentially be discovered.

Agent-based simulation research benefits from the modular design of the embodied models. Therefore, the proposed model can be easily expanded by replacing individual bits and pieces to observe the impact on the model behavior. For instance, agents can be equipped with different, perhaps more complex, decision rules and utility functions. In the following, I show directions for further research by discussing several additions to the proposed model.

It has been briefly addressed in the previous section that the model deliberately abstracts from platform differentiation and market segmentation by assuming that agents have homogeneous preferences. Thus, in the limiting case of complete information and perfect rationality, all agents have an identical view on what is the 'best' technology. Relaxing this assumption would very much complicate the discussion of market efficiency: how could one speak of superior and inferior technologies if everyone had his own personal benchmark? Nevertheless, allowing for platform differentiation and heterogeneous preferences could further enhance our understanding of market tipping and technological lock-ins, as emphasized by Katz & Shapiro (1994):

> "Consumer heterogeneity and product differentiation tend to limit tipping and sustain multiple networks. If the rival systems have distinct features sought by certain consumers, two or more systems may be able to survive by catering to consumers who care more about product attributes than network size. Here, market equilibrium with multiple incompatible products reflects the social value of variety. In some cases—Apple vs. IBM computers, perhaps— important variety benefits might be lost through standardization. In other cases, such as VHS vs. Beta in videocassette recorders, any loss of variety seems a minor price to pay to achieve compatibility." (Katz & Shapiro 1994, p. 106)

In addition, future research could also address the effect of pricing. Many formal models on two-sided markets from the industrial organization literature focus on pricing choices (Rysman 2009), for instance, by analyzing the optimal pricing strategy from the perspective of the platform provider.[168] In contrast, the proposed model abstracts from any pricing issues by assuming that pricing differences are either insignificant or that all platforms are priced at the same level.[169] Both users and complementors aim to choose the platform that benefits them most, independent of cost arguments. The reasons for this assumption are twofold.[170] First, the assumption that platforms are not differentiated by price allows the model to fully concentrate on the role of platform quality and the interactions between users and complementors. Second, the assumption holds for many technological platforms that are based on non-proprietary technologies. Also, even with proprietary platforms, competing platforms providers often choose to match competitors' pricing (Zhu & Iansiti 2012). These arguments notwithstanding, the extensive industrial organization literature on pricing in two-sided markets could be utilized to examine this topic more closely.

In order to build a more complete model of technological path dependence, I encourage further studies to integrate other forms of self-reinforcing mechanisms into the model. For instance, software platforms in particular benefit from large economies of scale, given that the marginal cost for an additional user is close to zero. Hence, successful firms could be assumed to have more resources to invest in technology development, making their platform even more

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168 See in particular Economides & Katsamakas (2007), who analyze the implications of proprietary vs. open technology platforms for equilibrium prices, sales, profitability and social welfare.

169 Alternatively, in the case that pricing differences are to be considered, the platform quality could be interpreted as the net value of benefits minus costs.

170 See also the reasoning of Zhu & Iansiti (2012), whose model rests on similar assumptions.

successful. Other studies have highlighted the role of learning effects for these types of high-tech markets (Langer 2011; Farrell & Klemperer 2007, pp. 1977ff.). Therefore, both users and complementors could be modeled to become less likely to switch platforms over time. Lastly, additional research should account for the role of adaptive expectations, i.e., the fact that actors tend to act speculatively in a network externalities context (Sillanpää & Laamanen 2009). In the face of uncertainty regarding the prospects of their resource commitment, actors form expectations about the future market structure which influence their platform choice. Therefore, the model could be expanded to include an explicit representation of expectation formation, which would allow to explore the resulting feedback processes at the macro level.

In conclusion, the proposed simulation model opens up a plethora of fruitful avenues for future research on competing platforms and technological lock-ins in two-sided markets.

9.5 Summary and conclusion

The most prominent examples for technological path dependence fall into the realm of two-sided markets, for instance the competition between *VHS* and *Betamax* in the video format war, or *Microsoft Windows*' dominance in the PC market. Together with the emblematic QWERTY case, these examples all highlight the key role of indirect network effects for the development of technological lock-ins. However, despite a vast body of theoretical and empirical research founded upon the seminal works of Katz & Shapiro (1985) and Arthur (1989), still little is known about the necessary circumstances for technological path dependence in the presence of indirect network effects. The present study has addressed this research gap and explored the conditions under which two-sided markets lock in to inferior technology platforms.

On the basis of a thorough review of the theoretical literature on technological path dependence in chapter 2, the research question was derived and its scope refined to focus on selected factors of influence (chapter 3). In chapter 4, the choice of an agent-based simulation for this research project was discussed, highlighting the unique benefits of this methodological approach. Chapter 5 presented the conceptual model of competing technologies in the context of the classic 'hardware/software paradigm'. Chapter 6 introduced the emerging smartphone industry, which provided the background for the empirical micro-validation and calibration of the simulation model in chapter 7. Finally, chapter 8 described the design of experiments and discussed the simulation results. This final chapter has highlighted the theoretical and practical implications of the findings, and explored avenues for further research.

This dissertation contributes to the theoretical literature on technological path dependence by complementing existing empirical case studies with a formal simulation model. In contrast to Arthur's seminal work (1989) and other theoretical contributions, the proposed agent-based model is the first model to formally explain lock-ins to *inferior* technologies. Furthermore, it draws a more complete picture of technology competition in network industries and far exceeds the scope of other existing models. The simulation study explores in depth the conditions which either favor or prevent the occurrence of technological lock-ins in the presence of indirect network effects. By leveraging the unique strength of simulation research, the model is able to precisely identify the causal relationships and to quantify the probability for inferior market outcomes.

The existing literature on technological path dependence has largely ignored the impact of bounded rationality and imperfect information. For instance, Arthur's model (1989) is built on the premise that all agents have perfect information and strictly maximize their individual utility function. The proposed simulation model integrates the research on the boundedness of rationality and thus adds a new dimension to path dependence theory. The agent-based simulation study is able to analyze the non-linear diffusion processes at any level of detail with a longitudinal perspective, thereby tracing the sequence of decisions and critical events. The controlled research setting provides new insights into the contingent nature of seemingly insignificant decisions that ultimately trigger self-reinforcing dynamics. In contrast to other formal models that focus solely on self-reinforcement and market tipping, the present study also explores the genesis of 'small events' and links the concept to information imperfections and boundedly-rational behavior.

As a methodological contribution, the dissertation demonstrates the integration of qualitative and quantitative empirical research into a formal simulation model. Empirical evidence on the smartphone industry provided guidance during model building and was employed for the micro-validation and calibration of the model. The study makes use of a variety of research methods, ranging from computer-based simulation to a conjoint experiment, press analyses and qualitative interviews. Hence, the dissertation is a multi-method approach that required not only modeling and programming skills, but also expertise in qualitative and quantitative empirical research. This close link between the model and the empirical application has two distinct benefits. First, it serves to demonstrate that simulation modeling can go beyond empirically distant "toy models of actual phenomena, … [that] either replicate the obvious or strip away so much realism that they are simply too inaccurate to yield valid theoretical insights" (David et al. 2007, p. 480). Second, the empirical calibration is of benefit for the interpretation of the results. By operationalizing and calibrating abstract theoretical constructs, the explanatory power of the results is greatly enhanced with regard to their real-world implications. To illustrate, by empirically calibrating an abstract model parameter such as the strength of network effects, any identified tipping points of this parameter are given empirical substance: the model results can be transferred to their real-world counterpart more plausibly.

Lave & March (1993, pp. 51-77) argue that a good model requires truth, beauty and justice.

Truth implies that a model should be testable. While every effort has been made to provide a 'realistic' model of technological path dependence, it remains to be seen whether it provides correct assertions.

Beauty requires that the model be simple, general and unpredictable. The proposed model aims to be as simple as possible and as complex as necessary. It is applicable to a range of different industries, and it provides surprising results on the conditions for technological lock-ins.

Justice demands that the model contribute to making the world better, not worse. Platform markets which involve path-dependent competition dynamics are always at risk of ending up in inferior lock-ins. Given that platform markets play an increasingly important role in today's global economy, the findings of this dissertation are of particular relevance.

The economics of QWERTY have been the focus of a tremendous amount of scientific work. In a recent contribution to the *American Economic Review*, Hossain and Morgan once again call the validity of the QWERTY case into question:

> "The risk of QWERTY-type outcomes in platform competition is now accepted as conventional wisdom rather than something counterintuitive. While the QWERTY effect is certainly an interesting theoretical possibility, the dearth of examples of the phenomenon, both in the field and now in the lab, leads us to conclude that the danger lies more in the minds of theorists than in the reality of the marketplace". (Hossain & Morgan 2009, p. 440)

This dissertation has pointed out in detail the theoretical possibility for QWERTY-type outcomes and has added substantially to our understanding of technological path dependence. Path dependence scholars are encouraged to validate the relationships derived herein through further qualitative and quantitative research in order to underpin the theoretical findings originating from the artificial world of social simulation with further empirical evidence.

* * *

10 References

In the interest of clarity, the references for chapter 6 and appendix B (primarily press releases, newspaper articles etc.) on the empirical case are given separately in section 11.

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11 Additional references for the empirical case (chapter 6 & appendix B)

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Appendices

Appendix A Model documentation and source code

The model documentation below includes the source code for the agent implementations. The programming code for the graphical user interface, the database connection and other helper functions are omitted for brevity.

Model: PlatformCompetition_20110923

Name	Value
General	
Java Package Name	tgm.diss
File Name	D:\documents\promotion\anylogic\PlatformCompetition_20110923\PlatformCompetition_20110923.alp
Model Time	
Model Time Units	Week

Active Object Class: Main

Name	Value
General	
Startup Code	`// connect to mysql database` `if (Tech_SaveData != DatabaseWriter.OFF) {` `   //mysql_database.connect();` `   databaseWriter = new DatabaseWriter(getEngine());` `}` `// log info and error messages to file and console` `logger = new MessageLogger(getEngine());` `// diffusion` `//bassDiffusionHelper = new BassDiffusionHelper(getEngine().getRoot());` `customRandomDiffusion = new CustomRandom(1); // fixed seed ensures stable adoption pattern` `// create and initialize platforms, consumer agents and developer agents` `initAgents();`
Destroy Code	`// close database connection and log file handler` `if (Tech_SaveData != DatabaseWriter.OFF) {` `   databaseWriter.close();` `}` `logger.close();`
Advanced	
Additional Code	`public class SortUsersByNumberOfLinks implements Comparator<User>{` `   public int compare(User u1, User u2) {` `       // sorts by number of links descending` `       return (u2.numberOfLinks - u1.numberOfLinks);` `   }` `}`
Auto-create Datasets	false
Make Default View Area	false

Function: initAgents

Name	Value
General	
Return Type	void
Code	
Body	`// ------------------------------------------------------------------------------` `// PLATFORMS` `Platform pf = null;` `// list of platform qualities, to be sorted later` `ArrayList qualities = new ArrayList<Double>();`

```
// compute platform qualities from parameters
{
/*
- qualities are deterministic, based on two parameters: average quality and quality variation
- quality difference between platforms is equal
- qualities of worst and best platform are independent from the total number of platforms
*/

// absolute difference between worst and best platform
double diffWorstBest = Platform_AvgQuality * Platform_QualityVariation;

// quality of worst platform
double worst = Platform_AvgQuality - (diffWorstBest / 2);

// quality differences between platforms
double diffBetweenPlatforms = diffWorstBest / (Env_NumPlatforms - 1);

for (int i = 0; i < Env_NumPlatforms; i++) {
   Double q = new Double(worst + (diffBetweenPlatforms * i));
   qualities.add(q);
}

// sort platforms by descending quality
// platform 1 is always the best platform
Collections.sort(qualities);
Collections.reverse(qualities);
}

// compute entry timing from parameters

// difference between first and last entrant in model timesteps
double entryDiffFirstLast = Env_Timesteps * Platform_EntryTimingVariation;

// last market entry
double last = entryDiffFirstLast;

// entry timing differences between platforms
double entryDiffBetweenPlatforms = entryDiffFirstLast / (Env_NumPlatforms - 1);

// rename platforms: A (best quality, latest entrance) to E (worst quality, first entrance)
char platformIDs[] = new char[]{'A','B','C','D','E'};

for (int i = 0; i < Env_NumPlatforms; i++) {

   double marketEntry = (last - (entryDiffBetweenPlatforms * i));
   double quality = ((Double)qualities.get(i)).doubleValue();

   // add platform object to simulation
   pf = add_platform("Platform " + platformIDs[i], marketEntry, quality, 0, false);
}

// see description of relative network effect below (consumer section)
// if network effect factor equals 1, network effect utility would be infinite -> set to .999
if (User_RelativeNetworkEffect == 1) {
   User_RelativeNetworkEffect = 0.999;
}
double utilUpperLimit = (User_RelativeNetworkEffect * Platform_AvgQuality) / (1 - User_RelativeNetworkEffect);

// chart statistics require five platforms: add dummy platforms in case we have fewer
while (platform.size() < 5) {
   pf = add_platform("DUMMY", 0, 0.0, 0, true);
}

// store market share history for each platform
for (Platform p : platform) {
   for (int i=0; i<=Env_Timesteps;i++) {
      p.marketShareTimetable.add(0);
   }
}

// -----------------------------------------------------------------------------
// CONSUMERS

User userAgent = null;

/*
Network effect factor: adapted from Buxmann 2001
c: network effect utility
b: basic utility
network effect factor (relative strength of network effect): q = c / (c + b) , 0..1
solved for c: c = (q * b) / ( 1 - q)
*/
```

```
// decision horizon is set relative to model lifetime
double decisionHorizon = User_DecisionHorizon * Env_Timesteps;

// consumers stick to their platform choice for at least 1 timestep
// would result in an infinite loop if decisionHorizon = 0,
if (decisionHorizon < 1) {
   decisionHorizon = 1;
}

// Bass diffusion
int adoptionTime = 0;

for (int i = 0; i < Env_ConsumerPopulation; i++) {
   // add platform object to simulation
   userAgent = add_user("U_" + (i+1), User_ExternalInfluence, User_WoM, -1, User_InformationLevel,
User_RationalityLevel,        User_SocialInfluenceSensitivity, utilUpperLimit, User_UtilGradient, decisionHorizon,
adoptionTime);
   userAgent.setEnvironment( user_environment );
}


// discards all existing connections
// establish new links according to the current network setting (e.g., scale-free)
user_environment.applyNetwork();

// update layout: rearranges agents in this environment according to the selected layout type (e.g., scale-free)
//user_environment.applyLayout(); // not necessary for batch runs, takes much time...

// compute link statistics
ArrayList<User> uSortable = new ArrayList<User>();

// store number of user agents with a certain number of links
int[] links = new int[Env_ConsumerPopulation];
for (User u : user) {
   int numLinks = u.getConnectionsNumber();
   u.numberOfLinks = numLinks;
   links[numLinks] = (links[numLinks]+1);
   uSortable.add(u);
}

/*
// display degrees and corresponding number of agents
for (int i = 0; i < links.length; i++) {
System.out.println(i + "#" + links[i]);
}
*/

// sort consumer agents depending on the number of links, most connected agents come first
Collections.sort(uSortable, new SortUsersByNumberOfLinks());

// top 10% connected agents are marked as hubs
int numHubs = (int)Math.floor(0.1 * Env_ConsumerPopulation);
//logger.info("# of hubs: " + numHubs);

int oi = 1;
for (User u : uSortable) {
   if (oi <= numHubs) {
      // hub agent
      u.Type = User.HUB;
   } else {
      // normal agent
      u.Type = User.STANDARD;
   }
   oi++;
//logger.info(u.AgentID + ":" + u.numberOfLinks + "(" + u.Type + ")");
}

// -------------------------------------------------------------------------------
// COMPLEMENTORS
Complementor developerAgent = null;

for (int i = 0; i < Env_DeveloperPopulation; i++) {
   developerAgent = add_developer("D_" + (i+1), Dev_ResourceIntensiveness, Dev_SynergyLevel, Dev_InformationLevel,
Dev_DecisionHorizon*Env_Timesteps);
   developerAgent.setEnvironment( dev_environment );
}


updateStats();
```

Function: computeHHI

Name	Value
General	
Return Type	double
Code	
Body	`// compute herfindahl hirschman index` `int adopters = user.adopters();` `double hhi = Math.pow(zidz(platform.get(0).numUsers, adopters),2.0) +` `Math.pow(zidz(platform.get(1).numUsers, adopters),2.0) +` `Math.pow(zidz(platform.get(2).numUsers, adopters),2.0) +` `Math.pow(zidz(platform.get(3).numUsers, adopters),2.0) +` `Math.pow(zidz(platform.get(4).numUsers, adopters),2.0);` `return hhi;`

Function: updateStats

Name	Value
General	
Return Type	void
Code	
Body	(see code below)

```
// set hasMostApps flag

int maxApps = -1;
for (Platform p : platform) {
   if (p.NumApps > maxApps) {
      maxApps = p.NumApps;
   }
}

for (Platform p : platform) {
   if (p.NumApps == maxApps) {
      p.hasMostApps = true;
   } else {
      p.hasMostApps = false;
   }
}


// check for dominance of any platform and set dominanceSince parameter
// repeated calls to this function are necessary for batch run
isDominant();

// compute installed base
for (Platform pf : platform) {
   pf.installedBase = zidz(pf.numUsers, user.adopters());
}

// compute market shares

// compute market shares in a given period -> used for dev choices
int now = (int)getEngine().time();
int window = (int)Math.round(Dev_InformationLevel * Env_Timesteps);

// compute number of total platform choices in the given timeframe
int choices = 0;
for (Platform pf : platform) {
   choices = choices + computeChoices(pf.marketShareTimetable, now - window, now);
}

for (Platform pf : platform) {
   // compute market share for each platform
   pf.marketShare = zidz(computeChoices(pf.marketShareTimetable, now - window, now), (double)choices);
}

// compute market share in last year -> used for presentation

// 52 weeks = approx. one year
window = 52;
// reset
choices = 0;
for (Platform pf : platform) {
   choices = choices + computeChoices(pf.marketShareTimetable, now - window, now);
}

for (Platform pf : platform) {
   pf.marketShareYearly = zidz(computeChoices(pf.marketShareTimetable, now - window, now), (double)choices);
}
```

	`` // compute strategy shares // reset strategy statistics strategyStats.clear(); // java arrays start at 0, but strategies start with 1 (single-homing) for (int i = 0; i<=5; i++) { strategyStats.add(0); } // summarize developers' multi-homing strategies for (Complementor d : developer) { int numHoming = d.SupportedPlatforms.size(); strategyStats.set(numHoming, strategyStats.get(numHoming)+1); } ```

Function: getNumApps

Name	Value
General	
Return Type	int
Code	
Body	`// calculate total number of apps` `int apps = 0;` `for (Platform p : platform) {` `   apps += p.NumApps;` `}` `return apps;`

Function: computeMDTreshold

Name	Value
General	
Return Type	double
Code	
Body	see below

```
// compute melnik dominance treshold
// Source: Melnik et al. 2008: "Assessing market dominance"
// Journal of Economic Behavior & Organization 68 (2008) 63-72

// fill ArrayList with market shares (installed base)
ArrayList<Double> marketshares = new ArrayList<Double>();
for (Platform p : platform) {
   marketshares.add(new Double(p.installedBase));
}

// sort descending
Collections.sort(marketshares);
Collections.reverse(marketshares);

// dominance tolerance factor:
// a low value of 0.5 results in a high threshold for dominance
// platform 1 needs a substantial market share advantage over firm 2 to be classified as dominant
double y = 0.5;

// compute dominance treshold
double treshold = 0.5 * ( 1-y*( Math.pow(marketshares.get(0).doubleValue(), 2.0) -
Math.pow(marketshares.get(1).doubleValue(), 2.0) ) );

return treshold;
```

Function: computeChoices

Name	Value
General	
Return Type	int
Code	
Body	see below

```
/*
calculates the number of choices between time1 and time2
timetable: ArrayList with the number of choices in each timestep
*/

// data available since t=0
if (time1 < 0) {
   time1 = 0;
}

// add up choices between time1 and time2
```

	`` int choices = 0; for (int i = time1; i<=time2; i++) { choices = choices + (int)(Integer)timetable.get(i); } return choices; ```

Arguments:

Name	Type
timetable	ArrayList
time1	int
time2	int

Function: isPathdependent2ndDegr

Name	Value
General	
Return Type	boolean
Code	
Body	(see below)

```
// criteria
// dominance: installed based is greater than the treshold
// persistence: dominance for longer than x steps
// suboptimality: dominant platform is not the best platform

boolean pd2 = (isDominant() && isPersistent() && isSuboptimal());

if (pd2) {
   pathDependence2ndDegr = true;
} else {
   if (pathDependence2ndDegr) {
      // lost 2nd degree path dependence
      lostPathDependence2ndDegr = true;
   }
   pathDependence2ndDegr = false;
}

return pd2;
```

Function: isPathdependent3rdDegr

Name	Value
General	
Return Type	boolean
Code	
Body	(see below)

```
// criteria
// dominance: installed based is greater than the treshold
// persistence: dominance for longer than x steps
// suboptimality: dominant platform is not the best platform
// remediability: was there a better alternative when the now dominant platform was introduced?

boolean pd3 = (isDominant() && isPersistent() && isSuboptimal() && isRemediable());

if (pd3) {
   pathDependence3rdDegr = true;
} else {
   if (pathDependence3rdDegr) {
      // lost 3rd degree path dependence
      lostPathDependence3rdDegr = true;
   }
   pathDependence3rdDegr = false;
}

return pd3;
```

Function: isDominant

Name	Value
General	
Return Type	boolean
Code	
Body	(see below)

```
// dominance criterion: installed base is greater than the treshold

boolean dominant = false;

for (Platform p : platform) {

   //logger.log(p.getName() + ":" + p.installedBase + ":" + treshold);
```

```
   // share in installed base equals or is greater than 75%
   if (p.installedBase >= 0.75) {
      dominant = true;

      // treshold is reached for the first time
      if (p.isDominant == false) {
         p.dominantSince = getEngine().time();
         p.isDominant = true;
      }

   } else {

      // platform has lost its dominant position
      if (p.isDominant == true) {
         p.lostDominance = true;
         p.isDominant = false;
      }
   }
}

/*
// Melnik dominance treshold
double treshold = computeMDTreshold();

for (Platform p : platform) {

//logger.log(p.getName() + ":" + p.installedBase + ":" + treshold);

// I experienced floating-point errors when y=1, resulting in two dominant firms
// solved by adding .0000001 to the treshold which has no negative impact
if (p.installedBase > (treshold + 0.0000001)) {
   dominant = true;

   // treshold is reached for the first time
   if (p.isDominant == false) {
      p.dominantSince = getEngine().time();
      p.isDominant = true;
   }

} else {

   // platform has lost its dominant position
   if (p.isDominant == true) {
      p.lostDominance = true;
      p.isDominant = false;
   }
}

}
*/

return dominant;
```

Function: isPersistent

Name	Value
General	
Return Type	boolean
Code	
Body	see code below

```
// persistence criterion: dominance for longer than Env_PersistenceCriterion steps

boolean persistent = false;

for (Platform p : platform) {
   if (p.isDominant) {
      double duration = getEngine().time() - p.dominantSince;
      if (duration >= Env_PersistenceCriterion) {
         persistent = true;
      }
   }
}

return persistent;
```

Function: isSuboptimal

Name	Value
General	
Return Type	boolean

Code	
Body	see code below

```
// suboptimality criterion: dominant platform is not the best platform

boolean suboptimal = false;
for (Platform p : platform) {
   if (p.isDominant && !p.isBest) {
      suboptimal = true;
   }
}

return suboptimal;
```

Function: isRemediable

Name	Value
General	
Return Type	boolean
Code	
Body	see code below

```
// remediability criterion: was there a better alternative when the now dominant platform was introduced?

boolean remediable = false;

// get dominant platform
Platform dominant = null;
for (Platform p : platform) {
   if (p.isDominant) {
      dominant = p;
   }
}

// in case there is no dominant platform, return false;
if (dominant != null) {

   // is there a better platform which was introduced simultaneously or even earlier?
   for (Platform p : platform) {
      if ((p.Quality > dominant.Quality) && (p.MarketEntry <= dominant.MarketEntry)) {
         remediable = true;
      }
   }
}

return remediable;
```

Function: getTimeToLockin

Name	Value
General	
Return Type	int

Name	Value
Code	
Body	see code below

```
// calculate time to lockin

// return -1 if not in a lock-in
if (isPathdependent2ndDegr() || isPathdependent3rdDegr()) {

   // get dominant platform
   Platform dominant = null;
   for (Platform p : platform) {
      if (p.isDominant) {
         dominant = p;
      }
   }

   // dominantSince guaranteed to be set in case of lock-in
   double dt = dominant.dominantSince;

   // path dependence can only be stated in case of *persistent* dominance
   // add persistence treshold to the time of initial dominance
   int timetolockin = (int)Math.ceil(dt) + Env_PersistenceCriterion;

   return timetolockin;

} else {
   return -1;
}
```

Plain Variable: numAdopters

Name	Value
General	
Type	int
Initial Value	0

Plain Variable: numDevelopers

Name	Value
General	
Type	int
Initial Value	0

Plain Variable: pathDependence2ndDegr

Name	Value
General	
Type	boolean

Plain Variable: lostPathDependence2ndDegr

Name	Value
General	
Type	boolean

Plain Variable: pathDependence3rdDegr

Name	Value
General	
Type	boolean

Plain Variable: lostPathDependence3rdDegr

Name	Value
General	
Type	boolean

Plain Variable: customRandomDiffusion

Name	Value
General	
Type	java.util.Random

Collection: strategyStats

Name	Value
General	
Collection Class	java.util.ArrayList
Element Class	Integer

Environment: user_environment

Name	Value
General	
Enable Steps	true
Step Duration	1
After Step	updateStats(); // save interim results for each step? if (Tech_SaveData == DatabaseWriter.ALL) { databaseWriter.saveStepData(); } // max timesteps reached? -> stop simulation run if (getEngine().time() >= Env_Timesteps) { getEngine().finish(); }
Advanced	
Space Type	CONTINUOUS
Dynamic: Width	530
Dynamic: Height	250
Layout Type	SPRING_MASS
Network Type	SCALE_FREE

Network Type Apply On Startup	true
M	4

Environment: dev_environment

Name	Value
General	
Enable Steps	true
Advanced	
Space Type	CONTINUOUS
Dynamic: Width	0
Dynamic: Height	0
Layout Type	USER_DEF
Network Type	USER_DEF

User: user

Name	Value
General	
Type	User
Java Package Name	tgm.diss
Replication	0
Embedded Object Collection Type	ARRAY_LIST_BASED
Envelopes	user_environment

Embedded Object Parameters:

Name	Value
Type	0

Embedded Object Statistics:

Name	Type	Expression	Condition
adopters	count		(item.statechart.isStateActive(User.PotentialAdopter) == false)
potentialAdopters	count		item.statechart.isStateActive(User.PotentialAdopter)

Platform: platform

Name	Value
General	
Type	Platform
Java Package Name	tgm.diss
Replication	0
Embedded Object Collection Type	ARRAY_LIST_BASED

Embedded Object Parameters:

Name	Value
Dummy	false

Complementor: developer

Name	Value
General	
Type	Complementor
Java Package Name	tgm.diss
Replication	0
Embedded Object Collection Type	ARRAY_LIST_BASED
Envelopes	dev_environment

Embedded Object Statistics:

Name	Type	Expression	Condition
activeDevelopers	count		(item.statechart.isStateActive(Complementor.PotentialComplementor) == false)

Active Object Class: User

Name	Value
General	
Agent	true
Advanced	
Additional Code	public class SortByUtility implements Comparator<ChoiceAlternative>{ public int compare(ChoiceAlternative ca1, ChoiceAlternative ca2) { // sorts by utility descending //return (int)(ca2.utility - ca1.utility); return (int)(ca2.blurredUtility - ca1.blurredUtility); } }
Icon Top Group Persistent	false
Presentation Top Group Persistent	false
Auto-create Datasets	false
Make Default View Area	false
Agent	
Space Type	CONTINUOUS
Environment Defines Init Location	true
On Receive	receiveMessage(msg, sender);
Statechart Refs	[]
On Step	//get_Main().logger.log("ON STEP!");

Parameter: AgentID

Name	Value
General	
Type	String
Editor	
Editor Control	TEXT_BOX

Parameter: Bass_ExternalInfluence

Name	Value
General	
Type	double
Editor	
Editor Control	TEXT_BOX

Parameter: Bass_WoM

Name	Value
General	
Type	double
Editor	
Editor Control	TEXT_BOX

Parameter: Type

Name	Value
General	
Type	int
Default Value	0
Editor	
Editor Control	TEXT_BOX

Parameter: InformationLevel

Name	Value
General	
Type	double
Editor	
Editor Control	TEXT_BOX

Parameter: RationalityLevel

Name	Value
General	
Type	double
Editor	
Editor Control	TEXT_BOX

Parameter: SocialInfluenceSensitivity

Name	Value
General	
Type	double
Editor	
Editor Control	TEXT_BOX

Parameter: UtilLimit

Name	Value
General	
Type	double
Editor	
Editor Control	TEXT_BOX

Parameter: UtilGradient

Name	Value
General	
Type	double
Editor	
Editor Control	TEXT_BOX

Parameter: DecisionHorizon

Name	Value
General	
Type	double
Editor	
Editor Control	TEXT_BOX

Parameter: BassFunctionAdoptionTime

Name	Value
General	
Type	double
Editor	
Editor Control	TEXT_BOX

Function: choosePlatform

Name	Value
General	
Return Type	void
Code	
Body	(see code below)

```
// choose platform based on utility considerations
// ask neighbors in interpersonal network for platform recommendations
deliver("ASK_FOR_RECOMMENDATION", ALL_CONNECTED);

// messages are processed synchronously:
// at this point we will have received all responses
// and the recommended platforms have been included in the consideration set

// fill remaining slots of the consideration set with randomly selected platforms

// calculate number of available platforms
int numAvailable = 0;
for (Platform p : get_Main().platform) {
   if (p.isAvailable()) {
```

```
        numAvailable++;
    }
}

while ((considerationSet.size() < numAvailable) && (considerationSet.size() < considerationSetMaxSize)) {

    // pick a random platform
    int rand = uniform_discr(get_Main().platform.size()-1);
    Platform p = get_Main().platform.get(rand);

    // platform already in consideration set?
    boolean inCS = false;
    for (ChoiceAlternative ca : considerationSet) {
        if (p == ca.p) {
            inCS = true;
        }
    }

    if ((inCS == false) && (p.isAvailable())) {
        ChoiceAlternative ca = new ChoiceAlternative(p, get_Main());
        ca.recommendationBased = false;
        considerationSet.add(ca);
    }
}

// choose platform from consideration set
if (considerationSet.size() > 0) {

    // shuffle consideration set to guarantee random choice in case of equal utilities
    Collections.shuffle(considerationSet, getEngine().getDefaultRandomGenerator());

    int totalRecommendations = 0;
    for (ChoiceAlternative ca : considerationSet) {
        totalRecommendations += ca.recommendationScore;
    }

    for (ChoiceAlternative ca : considerationSet) {
        ca.computeUtility(get_Main().Platform_AvgQuality, RationalityLevel, UtilLimit, UtilGradient,
SocialInfluenceSensitivity, totalRecommendations);
    }


    // select platform with highest (perceived) utility
    Collections.sort(considerationSet, new SortByUtility());
    platform = considerationSet.get(0).p;
    platform.numUsers++;


} else {
    get_Main().logger.error("no platform available!");
}

// update stats
lastPlatformChoice = get_Main().getEngine().time();

// how many choices already took place in the current step?
int sumTimestep = platform.marketShareTimetable.get((int) lastPlatformChoice).intValue();
// increment by 1
platform.marketShareTimetable.set((int)lastPlatformChoice, new Integer(++sumTimestep));

// update hasMostUsers flag
int maxUsers = -1;
for (Platform p : get_Main().platform) {
    if (p.isAvailable() && (p.numUsers > maxUsers)) {
        maxUsers = p.numUsers;
    }
}

for (Platform p : get_Main().platform) {
    if (p.numUsers == maxUsers) {
        p.hasMostUsers = true;
    } else {
        p.hasMostUsers = false;
    }
}
```

Function: receiveMessage

Name	Value
General	
Return Type	void

Code	
Body	`// handles inter-agent communication` `//get_Main().logger.log("MSG RECEIVED FROM " + sender + ": " + msg);` `String sMsg = (String)msg;` `if (sMsg.equals("ASK_FOR_RECOMMENDATION")) {` `   if (platform == null) {` `      //deliver("GIVE_RECOMMENDATION:no_platform", sender);` `   } else {` `      deliver("GIVE_RECOMMENDATION:" + platform.PlatformID + "#" + getConnectionsNumber(), sender);` `   }` `} else if (sMsg.startsWith("GIVE_RECOMMENDATION")) {` `   String platformID = sMsg.substring(sMsg.indexOf(':')+1, sMsg.indexOf('#'));` `   int weight = Integer.parseInt(sMsg.substring(sMsg.indexOf('#')+1));` `   if (platformID.equals("no_platform")) {` `      // the answering agent has not yet chosen a platform` `   } else {` `      handleRecommendation(platformID, weight);` `   }` `} else {` `   // forward to statechart` `   statechart.receiveMessage(msg);` `}`

Arguments:

Name	Type
msg	java.lang.Object
sender	AgentContinuous2D

Function: handleRecommendation

Name	Value
General	
Return Type	void
Code	
Body	`// process platform recommendation` `Platform pRecom = null;` `// get platform object for ID` `for (Platform p : get_Main().platform) {` `   if (p.PlatformID.equals(platformID)) {` `      pRecom = p;` `      break;` `   }` `}` `boolean alreadyInCS = false;` `// platform already in consideration set?` `for (ChoiceAlternative ca : considerationSet) {` `   if (pRecom == ca.p) {` `      // increment number of recommendations for that platform` `      ca.recommendationScore = ca.recommendationScore + weight;` `      alreadyInCS = true;` `   }` `}` `// consideration set already full?` `if (!alreadyInCS && (considerationSet.size() < considerationSetMaxSize)) {` `   // add to consideration set` `   ChoiceAlternative ca = new ChoiceAlternative(pRecom, get_Main());` `   ca.recommendationBased = true;` `   ca.recommendationScore = weight;` `   considerationSet.add(ca);` `} else {` `   //get_Main().logger.log("consideration set: max size reached!");` `}`

Arguments:

Name	Type
platformID	String
weight	int

Function: reconsiderPlatformChoice

Name	Value
General	
Return Type	void
Code	
Body	`// re-evaluate platform alternatives` `// reset` `considerationSet.clear();` `platform.numUsers--;` `// choose new platform` `choosePlatform();`

Function: init

Name	Value
General	
Return Type	void
Code	
Body	`// word of mouth disabled by default, gets enabled as soon as the user becomes an adopter` `WoM_Event.reset();` `// limit size of consideration set depending on parameter` `considerationSetMaxSize = (int)Math.round(InformationLevel * get_Main().Env_NumPlatforms);` `if (considerationSetMaxSize < 1) {` `   considerationSetMaxSize = 1;` `}`

Event: WoM_Event

Name	Value
General	
Trigger Type	timeout
Mode	cyclic
Recurrence	exponential(Bass_WoM, 0, get_Main().customRandomDiffusion)
Occurence Time	exponential(Bass_WoM, 0, get_Main().customRandomDiffusion)
Action	`deliver("ADOPT!", RANDOM_CONNECTED);` `get_Main().womcount++;`

Plain Variable: platform

Name	Value
General	
Type	Platform

Plain Variable: adoptionTrigger

Name	Value
General	
Type	int

Plain Variable: lastPlatformChoice

Name	Value
General	
Type	double

Plain Variable: numberOfLinks

Name	Value
General	
Type	int

Plain Variable: adoptionTime

Name	Value
General	
Type	double

Plain Variable: HUB

Name	Value
General	

Static	true
Constant	true
Type	int
Initial Value	1

Plain Variable: STANDARD

Name	Value
General	
Static	true
Constant	true
Type	int
Initial Value	2

Plain Variable: considerationSetMaxSize

Name	Value
General	
Type	int

Collection: considerationSet

Name	Value
General	
Collection Class	java.util.ArrayList
Element Class	ChoiceAlternative

Statechart Entry Point: statechart

Name	Value
General	
Show name	false
Action	init()

Transition: ExternalInfluence

Name	Value
General	
Show name	true
Trigger Type	timeout
Timeout	exponential(Bass_ExternalInfluence, 0, get_Main().customRandomDiffusion)
Action	adoptionTrigger = 1; get_Main().numAdoptersFromAd++;
Guard	get_Main().extGuard

Transition: ChoosePlatform

Name	Value
General	
Show name	true
Action	choosePlatform()

Transition: ReconsiderPlatformChoice

Name	Value
General	
Show name	true
Trigger Type	timeout
Timeout	DecisionHorizon

Name	Value
Action	reconsiderPlatformChoice()
Guard	(DecisionHorizon > 0)

Transition: WordOfMouth

Name	Value
General	
Show name	true
Trigger Type	message
Message Type	Object
Filter Type	equalsTo

Equals	"ADOPT!"
Action	adoptionTrigger = 2; get_Main().numAdoptersFromWOM++;
Guard	true

State: PotentialAdopter

Name	Value
General	
Exit Action	get_Main().numAdopters++; adoptionTime = get_Main().getEngine().time(); WoM_Event.restart(); // begin with word of mouth

State: Adopter

Active Object Class: Platform

Name	Value
Advanced	
Auto-create Datasets	true
Recurrence	1
Dataset Samples To Keep	100
Make Default View Area	false

Parameter: PlatformID

Name	Value
General	
Type	String
Editor	
Editor Control	TEXT_BOX

Parameter: MarketEntry

Name	Value
General	
Type	double
Editor	
Editor Control	TEXT_BOX

Parameter: Quality

Name	Value
General	
Type	double
Editor	
Editor Control	TEXT_BOX

Parameter: NumApps

Name	Value
General	
Type	int
Editor	
Editor Control	TEXT_BOX

Parameter: Dummy

Name	Value
General	
Type	boolean
Default Value	false
Editor	
Editor Control	CHECK_BOX

Function: isAvailable

Name	Value
General	
Return Type	boolean
Code	
Body	// is platform available, i.e. on the market? return statechart.isStateActive(OnTheMarket);

Function: enterMarket

Name	Value
General	
Return Type	void
Code	
Body	see code below

```
// update isBest flag
double bestQual = -1.0;
for (Platform p : get_Main().platform) {
   if (p.isAvailable() && (p.Quality > bestQual)) {
      bestQual = p.Quality;
   }
}

for (Platform p : get_Main().platform) {
   if (p.Quality == bestQual) {
      p.isBest = true;
   } else {
      p.isBest = false;
   }
}
```

Function: toString

Name	Value
General	
Access Type	public
Return Type	String
Code	
Body	return PlatformID;

Plain Variable: numUsers

Name	Value
General	
Type	int

Plain Variable: isBest

Name	Value
General	
Type	boolean

Plain Variable: hasMostApps

Name	Value
General	
Type	boolean

Plain Variable: hasMostUsers

Name	Value
General	
Type	boolean

Plain Variable: installedBase

Name	Value
General	
Type	double

Plain Variable: numDevelopers

Name	Value
General	
Type	int

Plain Variable: marketShare

Name	Value
General	
Type	double

Plain Variable: marketShareYearly

Name	Value
General	
Type	double

Plain Variable: isDominant

Name	Value
General	
Type	boolean

Plain Variable: dominantSince

Name	Value
General	
Type	double

Plain Variable: lostDominance

Name	Value
General	
Type	boolean

Plain Variable: expectationDuration

Name	Value
General	
Type	double
Initial Value	50

Plain Variable: expectedMarketShare

Name	Value
General	
Type	double

Collection: marketShareTimetable

Name	Value
General	
Collection Class	java.util.ArrayList
Element Class	Integer

Statechart Entry Point: statechart

Name	Value
General	
Show name	false
Action	// disable Lose_SuccessExpectation.reset();

Transition: EnterMarket

Name	Value
General	
Show name	true
Trigger Type	timeout
Timeout	MarketEntry
Guard	(Dummy == false)

Transition: ExitMarket

Name	Value
General	
Show name	true
Trigger Type	condition
Condition	false

State: InDevelopment

State: OnTheMarket

Name	Value
General	
Entry Action	enterMarket();

State: EndOfLife

Active Object Class: Complementor

Name	Value
General	
Agent	true
Advanced	
Icon Top Group Persistent	false
Presentation Top Group Persistent	false
Auto-create Datasets	false
Make Default View Area	false
Agent	
Space Type	CONTINUOUS
Environment Defines Init Location	true
Statechart Refs	[]

Parameter: AgentID

Name	Value
General	
Name	Value
Type	String
Editor	
Editor Control	TEXT_BOX

Parameter: RessourceIntensiveness

Name	Value
General	
Type	double
Editor	
Editor Control	TEXT_BOX

Parameter: SynergyLevel

Name	Value
General	
Type	double
Editor	
Editor Control	TEXT_BOX

Parameter: InformationLevel

Name	Value
General	
Type	double
Editor	
Editor Control	TEXT_BOX

Parameter: DecisionHorizon

Name	Value
General	
Type	double
Editor	
Editor Control	TEXT_BOX

Function: startDevelopment

Name	Value
General	

Return Type	void
Code	
Body	// wait until development cycle has finished // see transition: FinishDevelopment

Function: choosePlatforms

Name	Value
General	
Return Type	void
Code	
Body	(see code below)

```
// choose the optimal platform strategy

// update stats to make sure that up-to-date market share information is used
get_Main().updateStats();
// reset
SupportedPlatforms.clear();
developmentCycleRuns = 0;

// only active platforms can be chosen for development
ChoiceSet = new ArrayList<ChoiceAlternative>();
for (Platform p : get_Main().platform) {
   if (p.isAvailable()) {
      ChoiceSet.add(new ChoiceAlternative(p, get_Main()));
   }
}

if (ChoiceSet.isEmpty()) {
   get_Main().logger.error("DEV: no platform available");
   return;
}

// shuffle choice set to guarantee random choice in case of equal market shares
Collections.shuffle(ChoiceSet, getEngine().getDefaultRandomGenerator());

ChoiceAlternative newentrant = null;

// form decision basis
for (ChoiceAlternative ca : ChoiceSet) {

   ca.installedBase = ca.p.installedBase;
   ca.marketShare = ca.p.marketShare;

   // if information level is set to 1, use installed base (=perfect information)
   if (get_Main().Dev_InformationLevel == 1.0) {
      ca.decisionBasis = ca.installedBase;
   } else {
      ca.decisionBasis = ca.marketShare;
   }

   //get_Main().logger.log(ca.p.PlatformID + ": " + ca.decisionBasis + " (actual)");
}

//sort choice alternatives descending according to estimated market shares
Collections.sort(ChoiceSet);

// single-homing or multi-homing strategy? -> maximize expected reach
int maxHoming = ChoiceSet.size(); // normally five

StringBuffer rt = new StringBuffer();
rt.append("Estimated reach:\n");

// in case all market shares are 0% do single-homing on a random platform
int bestHoming = 1;
double maxReach = 0.0;

// evaluate strategies (single-homing, double..., triple...)
for (int i = 1; i <= maxHoming; i++) {
   // calculate estimated reach with a given strategy
   double reach = calcEstimatedReach(i);
   if (reach > maxReach) {
      maxReach = reach;
      bestHoming = i;
   }
   // update debug information
   rt.append(i + " Platform(s): " + get_Main().format2(reach) + "\n");
}
Text_Reach.setText(rt.toString());

//get_Main().logger.log("Strategy: " + bestHoming + " platforms");
```

	`// support largest x platforms, depending on the chosen homing strategy` `for (int i = 0; i < bestHoming; i++) {` `   ChoiceAlternative ca = ChoiceSet.get(i);` `   SupportedPlatforms.add(ca.p);` `   //get_Main().logger.log(ca.p.PlatformID);` `}` `// how long does a development cycle take?` `// set timeout for state change accordingly` `timestepsForDevelopmentCycle = calcDevCycle(SupportedPlatforms.size());` `// update statistics` `for (Platform p : SupportedPlatforms) {` `   p.numDevelopers++;` `}`

Function: finishDevelopment

Name	Value
General	
Return Type	void
Code	
Body	`// update statistics` `developmentCycleRuns++;` `for (Platform p : SupportedPlatforms) {` `   if (p.isAvailable()) {` `      // upscale impact of one complementor to match empirical findings` `      //p.numApps++;` `      p.NumApps = p.NumApps + 250;` `   }` `}`

Function: calcEstimatedReach

Name	Value
General	
Return Type	double
Code	
Body	`// calculate estimated reach with a given homing strategy` `double appsPerDecisionHorizon = 0.0;` `if (DecisionHorizon > 0) {` `   appsPerDecisionHorizon = DecisionHorizon / calcDevCycle(numHoming);` `} else {` `   // with an infinite decision horizon (i.e. no switching) calculate reach for 1000 steps` `   // as the decision horizon does not impair the strategy choice` `   appsPerDecisionHorizon = 1000 / calcDevCycle(numHoming);` `}` `double reach = 0.0;` `int adopters = get_Main().user.adopters();` `for (int i = 0; i < numHoming; i++) {` `   // choice set is sorted, take into account the market shares of the numHoming largest platforms` `   ChoiceAlternative ca = (ChoiceAlternative)ChoiceSet.get(i);` `   reach += appsPerDecisionHorizon * ca.decisionBasis * adopters;` `}` `return reach;`

Arguments:

Name	Type
numHoming	int

Function: calcDevCycle

Name	Value
General	
Return Type	double
Code	
Body	`// calculate length of development cycle with a given homing strategy,` `// considering development synergies between the platforms` `double resources = (1/(double)numHoming) * (1 + (get_Main().Dev_SynergyLevel * (numHoming - 1)) );`

	return (get_Main().Dev_ResourceIntensiveness / resources);

Arguments:

Name	Type
numHoming	int

Function: reconsiderPlatformChoice

Name	Value
General	
Return Type	void
Code	
Body	// update statistics for (Platform p : SupportedPlatforms) { p.numDevelopers--; }

Function: isReconsiderationScheduled

Name	Value
General	
Return Type	boolean
Code	
Body	// start next development cycle or re-evaluate platform strategy? if ((timestepsForDevelopmentCycle * developmentCycleRuns) >= DecisionHorizon) { // reconsider platform choice now return true; } else { // stick to platform strategy for another development cycle return false; }

Function: isTimeToEnterMarket

Name	Value
General	
Return Type	boolean
Code	
Body	// define market entry timing of developers // calculate adoption shares double userAdoptionFraction = zidz(get_Main().user.adopters(), get_Main().user.size()); double devAdoptionFraction = zidz(get_Main().developer.activeDevelopers(), get_Main().developer.size()); // developers enter market early, consumers follow (e.g., consumers: 2%, devs: 20%) int devDiffusionSpeedMultiple = 10; // enter market if (userAdoptionFraction > devAdoptionFraction / devDiffusionSpeedMultiple) { return true; } else { return false; }

Function: enterMarket

Name	Value
General	
Return Type	void
Code	
Body	// update statistics get_Main().numDevelopers++;

Plain Variable: timestepsForDevelopmentCycle

Name	Value
General	
Type	double
Initial Value	-1

Plain Variable: developmentCycleRuns

Name	Value
General	
Type	int
Initial Value	0

Collection: SupportedPlatforms

Name	Value
General	
Collection Class	java.util.ArrayList
Element Class	Platform

Collection: ChoiceSet

Name	Value
General	
Collection Class	java.util.ArrayList
Element Class	ChoiceAlternative

Statechart Entry Point: statechart

Name	Value
General	
Show name	false
Action	get_Main().computeMDTreshold()

Transition: FollowUsers

Name	Value
General	
Trigger Type	rate
Rate	1

Transition: EnterMarket

Name	Value
General	
Show name	true
Condition	isTimeToEnterMarket()
Action	enterMarket()

Transition: ChoosePlatforms

Name	Value
General	
Show name	true
Trigger Type	condition
Condition	true
Action	choosePlatforms()

Transition: StartDevelopment

Name	Value
General	
Show name	true
Trigger Type	condition
Condition	(SupportedPlatforms.isEmpty() == false)

Transition: FinishDevelopment

Name	Value
General	
Show name	true
Trigger Type	timeout
Timeout	timestepsForDevelopmentCycle
Action	finishDevelopment();

Transition: transition

Name	Value
General	
Trigger Type	condition

Condition	true

Transition: ReconsiderPlatformChoice

Name	Value
General	
Show name	true
Condition	isReconsiderationScheduled()
Action	reconsiderPlatformChoice()

Transition: StartNextDevelopmentCycle

Name	Value
General	
Show name	true

Transition: RepeatIfPlatformsUnavailable

Name	Value
General	
Show name	true
Show At Runtime	false
Trigger Type	timeout
Timeout	1

Transition: Wait

Name	Value
General	
Show name	true

State: PotentialComplementor

State: Complementor

State: PlatformsSupporter

State: InDevelopment

Name	Value
General	
Entry Action	startDevelopment()

State: EndOfDevelopmentCycle

Branch: IsMarketSizeAttractive

Name	Value
General	
Show name	true

Branch: DecisionHorizonReached

Name	Value
General	
Show name	true

Java Class: ChoiceAlternative

Name	Value
General	
Java Class Type	JAVA_CLASS
Text	import java.text.NumberFormat; import com.xj.anylogic.engine.ActiveObject; public class ChoiceAlternative implements java.io.Serializable, Comparable<ChoiceAlternative> { public Platform p; private Main main = null; // used for consumer choice public double basicUtility = 0.0; public double networkUtility = 0.0; public double utility = 0.0; public double blurredUtility = 0.0; public boolean recommendationBased = false; public int recommendationScore = 0;

```
// used for developer choice
public double marketShare = -1.0;
public double installedBase = -1.0;
public double decisionBasis = -1.0;


   public ChoiceAlternative(Platform p, Main m) {
    this.p = p;
    this.main = m;
   }

   public double computeUtility(double Platform_AvgQuality, double RationalityLevel, double UtilLimit, double
UtilGradient, double SocialInfluenceSensitivity, int TotalRecommendations) {

double qualityPerceptionBias = 1 - RationalityLevel;

// Have there been any recommendations by the agent's social network?
if (TotalRecommendations > 0) {
   // yes
   //basicUtility = (1 + SocialInfluenceSensitivity * (recommendationScore / TotalRecommendations)) * p.Quality;
   basicUtility = p.Quality;
   basicUtility += SocialInfluenceSensitivity * (recommendationScore / TotalRecommendations) * Platform_AvgQuality;
} else {
   // no, probably the decision of the first agent
   basicUtility = p.Quality;
}

   //networkUtility = (1 - Math.exp(-0.00005 * p.NumApps));
   networkUtility = (UtilLimit - UtilLimit*Math.exp(-UtilGradient/1000 * p.NumApps));

utility = basicUtility + networkUtility;

blurredUtility = utility + main.normal(qualityPerceptionBias * 0.5 * Platform_AvgQuality, 0.0);

/*
System.out.println("Platform: " + p.PlatformID);
System.out.println("Quality: " + p.Quality);
System.out.println("SocialInfluenceSensitivity: " + SocialInfluenceSensitivity);
System.out.println("RecommendationScore: " + recommendationScore);
System.out.println("Total recommendations: " + TotalRecommendations);
System.out.println("Basic utility: " + basicUtility);
System.out.println("Network utility: " + networkUtility);
System.out.println("Utility: " + utility);
System.out.println("Perceived utility: " + blurredUtility);
System.out.println("========================================");
*/

return blurredUtility;
   }

   @Override
   public int compareTo(ChoiceAlternative ca) {
    if (this.decisionBasis > ca.decisionBasis) {
    return -1;
    } else if (this.decisionBasis < ca.decisionBasis) {
    return 1;
    } else {
    return 0;
    }
   }


@Override
public String toString() {
NumberFormat nf = NumberFormat.getInstance();
nf.setMinimumFractionDigits(0);
nf.setMaximumFractionDigits(0);

if (decisionBasis > -1.0) {
// developer choice
return p.toString() + "(MS:" + nf.format(marketShare) + " IB:" + nf.format(installedBase) + ")";
} else {
// user choice
return "" + p.PlatformID.charAt(p.PlatformID.length()-1) + " U:" + nf.format(blurredUtility) + " BU:" +
nf.format(basicUtility) + " NU:" + nf.format(networkUtility) + " R:" + recommendationScore;
}
}

/**
* This number is here for model snapshot storing purpose<br>
* It needs to be changed when this class gets changed
*/
private static final long serialVersionUID = 1L;
```

	}

Java Class: CustomRandom

Name	Value
General	
Java Class Type	JAVA_CLASS
Text	import java.util.Random; public class CustomRandom extends Random { long seed; public CustomRandom() { // same seed logic as the default number generator in java.lang.Random long s = System.currentTimeMillis(); this.seed = s; super.setSeed(seed); } public CustomRandom(long s) { this.seed = s; super.setSeed(seed); } public String toString() { return "" + seed; } }

Simulation Experiment: Simulation

Name	Value
General	
Active Object Class	Main
Random Number Generation Type	customGenerator
Custom Generator Code	new CustomRandom()
Advanced	
Maximum Available Memory	256
Before Each Experiment Run	// use timestamp as experiment ID String DATE_FORMAT = "yyyyMMdd_HHmmss"; java.text.SimpleDateFormat sdf = new java.text.SimpleDateFormat(DATE_FORMAT); java.util.Calendar c1 = java.util.Calendar.getInstance(); // today getExperiment().setName("EXP_" + sdf.format(c1.getTime()));
After Simulation Run	int savedata = ((Main)getEngine().getRoot()).Tech_SaveData; // save parameter settings and results in database? if (savedata != DatabaseWriter.OFF) { DatabaseWriter db = ((Main)getEngine().getRoot()).databaseWriter; db.saveRunParams(); // in case of savedata=DatabaseWriter.ALL, step data has already been saved // (see Main->user_environment->On after step) if (savedata == DatabaseWriter.RESULTS_ONLY) { db.saveStepData(); } } ((Main)getEngine().getRoot()).editbox.setText(getExperiment().getName()); /* int notify = ((Main)getEngine().getRoot()).Tech_MailNotification; // experiment finished? send notification by mail if ((notify == MailNotifier.ON) && (getCurrentIteration() == getMaximumIterations())) { MailNotifier.sendMail(); } */
Differention Equations Method	EULER
Mixed Equations Method	RK45_NEWTON
Algebraic Equations Method	MODIFIED_NEWTON
Absolute Accuracy	1.0E-5

Time Accuracy	1.0E-5
Relative Accuracy	1.0E-5
Fixed Time Step	0.0010
Presentation Top Group Persistent	false
Model Time	
Use Calendar	true
Stop Option	Never
Initial Time	0.0
Final Time	1000.0
Initial Date	Mon Jan 01 00:00:00 GMT 2001
Presentation	

Name	Value
CPU Time Balance	ratio_1_2
Execution Mode	virtualTime
Window	
Title	Simulation: Path dependence in two-sided markets
File	true
Animation setup	true
View	true

Plain Variable: setup_env_consumerPopulation

Name	Value
General	
Type	int
Initial Value	500

Plain Variable: setup_dev_resourceIntensiveness

Name	Value
General	
Type	double
Initial Value	13

Plain Variable: setup_env_developerPopulation

Name	Value
General	
Type	int
Initial Value	50

Plain Variable: setup_user_rationalityLevel

Name	Value
General	
Type	double
Initial Value	0.7

Plain Variable: setup_user_informationLevel

Name	Value
General	
Type	double
Initial Value	0.37

Plain Variable: setup_dev_synergyLevel

Name	Value
General	
Type	double
Initial Value	0.3

Plain Variable: setup_platform_qualityVariation

Name	Value
General	
Type	double
Initial Value	0.678

Plain Variable: setup_user_wom

Name	Value
General	
Type	double
Initial Value	0.025

Plain Variable: setup_user_externalInfluence

Name	Value
General	
Type	double
Initial Value	0.000004

Plain Variable: setup_env_timesteps

Name	Value
General	
Type	int
Initial Value	1300

Plain Variable: setup_user_decisionHorizon

Name	Value
General	
Type	double
Initial Value	0.08

Plain Variable: setup_dev_decisionHorizon

Name	Value
General	
Type	double
Initial Value	0.04

Plain Variable: setup_dev_informationLevel

Name	Value
General	
Type	double
Initial Value	1.0

Plain Variable: setup_env_numPlatforms

Name	Value
General	
Type	int
Initial Value	5

Plain Variable: setup_platform_avgQuality

Name	Value
General	
Type	double
Initial Value	202.461

Plain Variable: setup_user_socialInfluenceSensitivity

Name	Value
General	
Type	double
Initial Value	0.0

Plain Variable: setup_user_relativeNetworkEffect

Name	Value
General	
Type	double
Initial Value	0.295

Plain Variable: setup_user_utilGradient

Name	Value
General	

Type	double
Initial Value	0.344

Plain Variable: setup_platform_entryTimingVariation

Name	Value
General	
Type	double
Initial Value	0.0

Plain Variable: setup_env_persistenceCriterion

Name	Value
General	
Type	int
Initial Value	100

Plain Variable: setup_platform_successExpectations

Name	Value
General	
Type	double
Initial Value	0.0

Parameter Variation Experiment: BatchRun

Name	Value
General	
Active Object Class	Main
Random Number Generation Type	customGenerator
Custom Generator Code	new CustomRandom()
Use Freeform Parameters	false
Number Of Runs	0
Advanced	

Name	Value
Maximum Available Memory	1024
Before Each Experiment Run	// use timestamp as experiment ID String DATE_FORMAT = "yyyyMMdd_HHmmss"; java.text.SimpleDateFormat sdf = new java.text.SimpleDateFormat(DATE_FORMAT); java.util.Calendar c1 = java.util.Calendar.getInstance(); // today getExperiment().setName("EXP_" + sdf.format(c1.getTime()));
After Simulation Run	int savedata = ((Main)getEngine().getRoot()).Tech_SaveData; // save parameter settings and results in database? if (savedata != DatabaseWriter.OFF) { DatabaseWriter db = ((Main)getEngine().getRoot()).databaseWriter; db.saveRunParams(); // in case of savedata=DatabaseWriter.ALL, step data has already been saved // (see Main->user_environment->On after step) if (savedata == DatabaseWriter.RESULTS_ONLY) { db.saveStepData(); } } ((Main)getEngine().getRoot()).editbox.setText(getExperiment().getName()); int notify = ((Main)getEngine().getRoot()).Tech_MailNotification; // experiment finished? send notification by mail and shutdown if ((notify == MailNotifier.ON) && (getCurrentIteration() == getMaximumIterations())) { MailNotifier.sendMail(); // shutdown Amazon EC2 instance to save money try { String shutdownCmd = "shutdown /s"; Process child = Runtime.getRuntime().exec(shutdownCmd); } catch (Exception e) { System.out.println("shutdown failed"); } }
Differention Equations Method	EULER
Mixed Equations Method	RK45_NEWTON

Algebraic Equations Method	MODIFIED_NEWTON
Absolute Accuracy	1.0E-5
Time Accuracy	1.0E-5
Relative Accuracy	1.0E-5
Fixed Time Step	0.0010
Model Time	
Stop Option	Never
Initial Time	0.0
Final Time	1000.0
Presentation	
CPU Time Balance	ratio_1_2
Window	
Title	BatchRun: Path dependence in two-sided markets
Model Time	false
Experiment Progress	true

Parameter Variation Experiment Parameters:

		Value		
Parameter	Type	Min	Max	Step
Env_Timesteps	FIXED	1300		
Env_NumPlatforms	FIXED	5		
Env_ConsumerPopulation	FIXED	500		
Env_DeveloperPopulation	FIXED	50		
Env_PersistenceCr	FIXED	100		

Parameter Variation Experiment Parameters:

		Value		
Parameter	Type	Min	Max	Step
iterion				
Platform_AvgQuality	FIXED	202.461		
Platform_QualityVariation	FIXED	0.678		
Platform_EntryTimingVariation	FIXED	0.0		
Platform_SuccessExpectations	FIXED	0.0		
User_ExternalInfluence	FIXED	0.000004		
User_WoM	FIXED	0.025		
User_InformationLevel	FIXED	0.37		
User_RationalityLevel	FIXED	0.7		
User_SocialInfluenceSensitivity	FIXED	0		
User_RelativeNetworkEffect	FIXED	0.295		
User_UtilGradient	FIXED	0.344		
User_DecisionHorizon	FIXED	0.08		
Dev_ResourceIntensiveness	FIXED	13		
Dev_SynergyLevel	FIXED	0.3		
Dev_InformationLevel	FIXED	1.0		
Dev_DecisionHorizon	FIXED	0.04		
Tech_Repetitions	RANGE	1	1500	1
Tech_SaveData	FIXED	1		
Tech_Logging	FIXED	4		
Tech_MailNotification	FIXED	1		

Appendix B A brief history of the smartphone industry

Despite the significance of the smartphone industry, a comprehensive historical overview is still lacking in the literature. To address this gap, this appendix outlines the origins and developments of the smartphone industry from a historical perspective and indicates important milestones.

The present empirical chapter is based heavily on data obtained from a systematic press analysis from January 2000 to March 2011. This analysis, undertaken jointly by the authors[171], focused on collecting relevant reports from various independent sources. News services were chosen to include publications from the business press, general newspapers and magazines, as well as weekly periodicals and IT industry news channels. The publications which were selected to cover major events and developments from a business perspective are the *Financial Times Deutschland* (German edition) and the *Economist*. Two general daily newspapers were selected, the *New York Times* and *The Guardian* (London), to cover both the European and the U.S. perspective. Furthermore, detailed IT industry coverage was obtained from *InformationWeek* and from the German online news service *Heise*. We performed a *LexisNexis* analysis of the abovementioned press, using a database query for the terms 'smartphone' and 'smartphones'; the analysis yielded the following results for the time frame from 16 February 2000 (starting date of the archives) to 31 March 2011 (end of data collection):

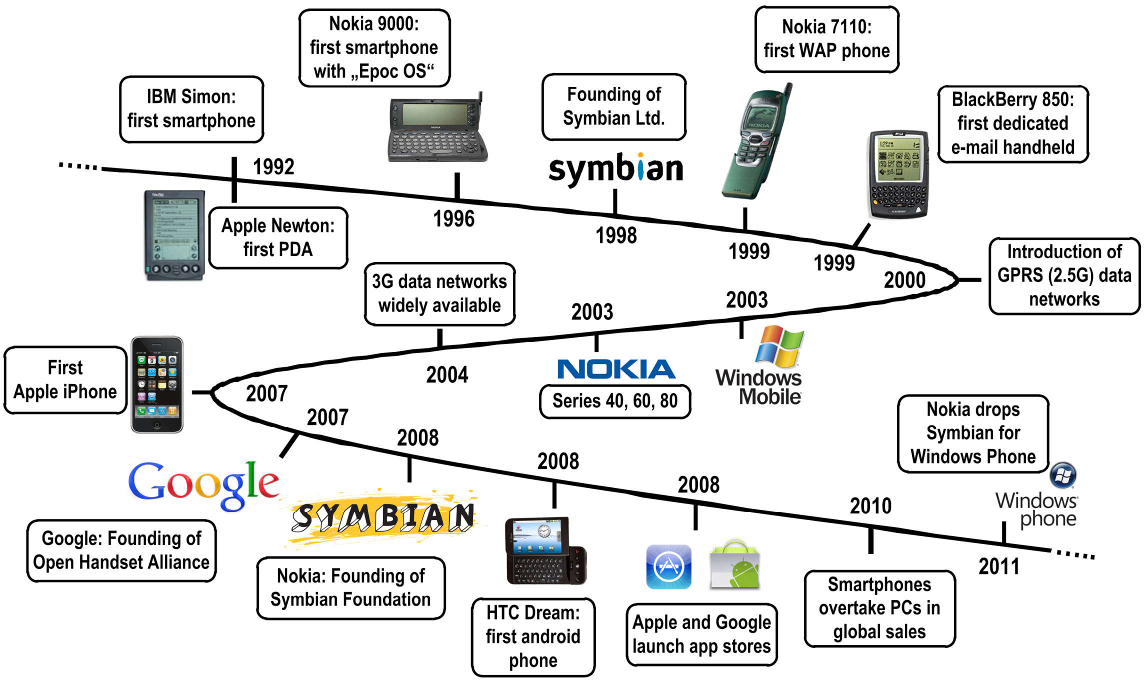
Table B-1 Summary of the LexisNexis press analysis

Publication	*Number of articles*
Financial Times Deutschland	436
The Economist	45
The New York Times	489
The Guardian (London)	220
InformationWeek	67
Total number of press articles	**1257**

171 This appendix was written in cooperation with Frithjof Stöppler.

In addition to the press analysis, various book sources and a vast number of online resources were consulted, especially for information on the early historical development of the industry. Turning now to the empirical case, Figure B-1 illustrates the major milestones that have shaped the smartphone industry.

Figure B-1 Historical milestones in the evolution of the smartphone industry



B.1 The early years: 1990 - 2000

The first smartphone was the *IBM Simon Personal Communicator*, developed by a joint venture between *IBM* and *Bell* (Evans et al. 2006). First shown at the COMDEX trade show in 1992, it was launched a year later exclusively in the USA, though it did not become commercially successful. At this time, personal computers had begun to considerably shrink in size and had become more powerful, which led to the appearance of laptops. The process of miniaturization reached new levels with *Apple's* 1992 introduction of the *Newton* personal digital assistant (PDA) (Greuling 2002, p. 694) and the founding of *Palm*, which became the most successful PDA manufacturer (Evans et al. 2006, p. 156). In the 1990s, GSM[172] was the first commercial digital

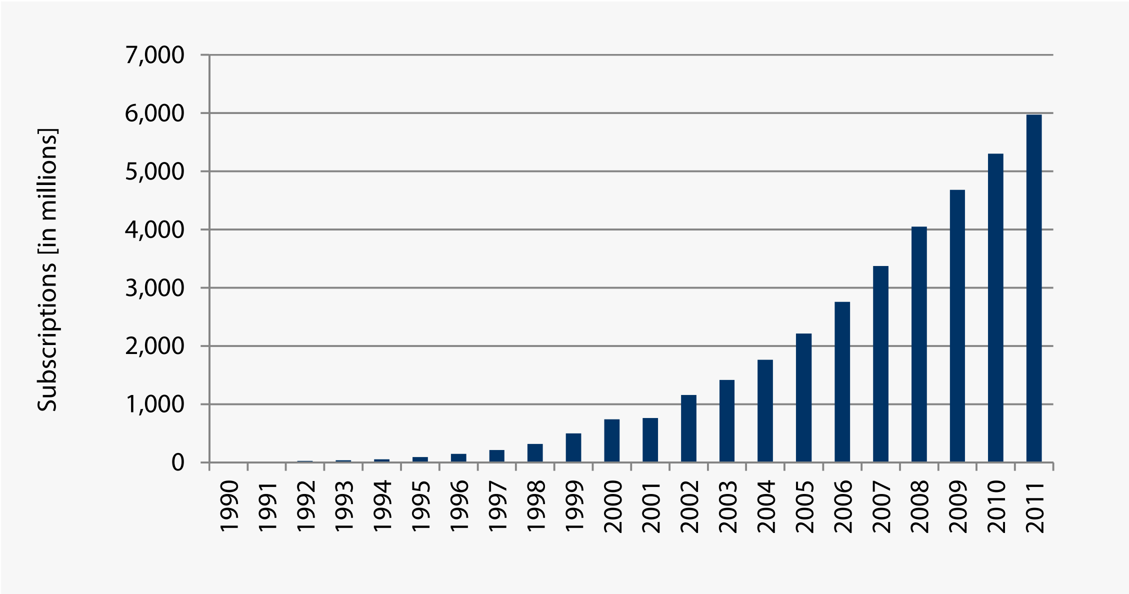
172 GSM: Global System for Mobile Communications

radio network standard. These so-called 'second generation mobile networks' (2G) replaced the first generation (1G) analogue networks (Tan & Teo 2005, p. 1985). They provided new features such as encrypted voice calls, SMS text messaging, and telefax. As a result of advances in technology, the portability of the devices used on these networks improved thanks to shrinking size and battery innovations.

Probably the most influential product for the emergence of the industry was the *Nokia 9000*, which was launched in 1996 as part of *Nokia's Communicator* product line (Evans et al. 2006, p. 184). This device was the first to combine phone and fax capabilities with contact management, text messaging, calendar, email and notepad functions, making it the first smartphone available on the global market. The term *smart phone* is said to have been used for the first time by *Ericsson* in 1997 for its *GS88* handset (SHSP 2011). After becoming very successful among professional users, the features of this mobile phone category spread to lower-priced devices at the end of the 1990s. As the demand for feature-rich phones increased, manufacturers started integrating technologies from other high-tech industries. Multimedia features such as MP3 players were integrated, as was the ability to access the World Wide Web. However, due to technology restrictions such as narrow bandwidth, small screen resolutions and slow processing power, the first phones could not access common HTML web pages. Consequently, the WAP[173] standard was developed in 1997. In the same year, the *WAP Forum* was founded in order to serve as a standardization body and spread the technology among member firms, which quickly increased in numbers (Klußmann 2001, pp. 1079-1080). At the same time, mobile phone services became available as prepaid packages without long-term billing arrangements. These tariffs enabled less wealthy people to use mobile phones and worldwide mobile subscriptions increased strongly, as shown in Figure B-2.

[173] WAP: Wireless application protocol

Figure B-2 **Mobile subscriptions worldwide 1990-2011**
(Source: ITU 1999, ITU 2002, ITU 2010, ITU 2012)



In 1998, market leader *Nokia* established *Symbian* as an industry consortium together with *Motorola, Ericsson* and *Psion* (Teather 2001, p. 28). The aim was to develop a joint, device-independent operating system, *Symbian OS*, on the basis on *Psion's* PDA operating system *EPOC* (Evans et al. 2006, p. 184). At the time, the members of the joint venture together covered 80 percent of the mobile phone market (Sosalla 2001, p. 4). In late 1999, *Nokia* introduced the first mobile phone with WAP capabilities. The technology was in such high demand that the phones became extremely scarce and the phrase: "WAP — Where are the phones?" became a popular saying among industry experts to describe this situation (Klußmann 2001, p. 1080). In the same year, *Research in Motion* (RIM) introduced its first email-dedicated mobile computer, the *Blackberry 850*. In Asian markets, mobile internet became popular more quickly than in the European and North American markets. Mobile internet flourished in Asia largely due to the success of the i-mode standard, a local competitor superior to WAP (Evans et al. 2006, p. 185). After WAP and i-mode were introduced, connection speeds were still low, so a need for higher speed radio technologies arose (Tan & Teo 2005, p. 1985). One of the so-called 2.5G technologies developed was HSCSD[174], which combined several time slots of conventional circuit-switched

[174] HSCSD: High Speed Circuit Switched Data.

connections. The second technology was GPRS[175], the first cellular network technology to utilize the packet-oriented data services from the internet world, rather than the circuit-switched methods from the telephone industry (Sauter 2011, p. 4). In the 2000s, HSCSD and GPRS were developed further to become EDGE[176], a data transmission technology still in operation at present. Asian and U.S. network operators used different technologies due to differences in frequency legislation. Their CDMA[177] standard offered slightly higher speeds and similar features while being technically incompatible with GSM. Intercontinental travelers thus had to change phones accordingly.

B.2 Gaining momentum: 2000 - 2007

The new millennium started with an important development in mobile communications. The third generation (3G) mobile radio licenses were granted to network operators, in many countries following an auction by the local radio administrative body. Winning operators committed themselves to multi-billion Euro license fees (e.g., €40 billion in Great Britain, €50 billion in Germany) and huge investments in network infrastructure. 3G networks became widely available in many countries in 2003/2004. These new data networks had become necessary because user numbers had grown so strongly that the available data traffic volume was becoming a restriction. In particular, increased internet use for accessing email, WAP, the new Multimedia Messaging Services (MMS) and media streaming required ever higher bandwidths (Tan & Teo 2005, p. 1986). Modern smartphones started to include a camera as well as audio and video players, thus integrating functionality beyond that of PDAs (Branscombe 2003, p. 14). Despite manufacturers adding features, demand rose for independent software producers to contribute their own software to add to the phones' functionality. *Motorola's i50sx* in 2001 was the first phone to integrate the capability to run simple Java applications, called MIDlets, which were used for, by today's standards, rather rudimentary productivity tools and games.

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175 GPRS: General Packet Radio Service.

176 EDGE: Enhanced Data rates for GSM Evolution.

177 CDMA: Code Division Multiple Access.

Microsoft's launch of *Windows Mobile* in 2002 indicated that operating systems had become an influential factor also for smartphones. *Microsoft* attracted *Motorola* as a licensee and *Motorola* consequently reduced its commitment to the *Symbian* joint venture. Shortly after, *Nokia* launched three different software architectures for mobile phones and smartphones, the *Series 40*, *60* and *80*. These versions were all based on *Symbian OS* (Evans et al. 2006, p. 184) and Samsung invested £17 million into the joint venture (Wray 2003, p. 24). This was the first time that operating systems were available that could be used across devices from different manufacturers. These events thus marked the beginning "of fierce struggle to establish the standard operating system for the next generation of mobile phones" (Teather 2001, p. 28).

Another competitor on the horizon was the PDA manufacturer *Palm*, who announced their *Palm OS*-based *Treo* handset in 2001 and later won *LG* as a licensee (Müller 2005, p. 131). With *Symbian, Microsoft* and *Palm* as the main competitors (Pogue 2003, p. 1), industry experts expected a showdown between the former two, who had the largest market share. "I think we have now got them all" said *Symbian* CEO David Levin (cited in: Lohmeyer 2002, p. 37) and *Symbian* appeared confident of winning the majority of device makers for their platform. Despite *Microsoft*'s aggressive marketing strategy (Borger & Kroder 2003, p. 4), *Symbian* did prove successful in selling licenses. For instance, this was evidenced when *Motorola*, a big *Microsoft* licensee, also launched a *Symbian*-based handset in 2003 (Economist 2003). Still, *Microsoft* expected high revenues from this fast growing market for smartphone operating systems (Wihofszki 2004, p. 4). *RIM*, whose operating system is exclusively used by its messaging-oriented smartphones under the *BlackBerry* brand, was mainly focused on the corporate market at this time (Young 2005, p. 22). *Microsoft* partnered with Taiwanese manufacturer *HTC* to produce phones for the same segment and their cooperation proved fruitful (Hille 2006, p. 7). Yet *Symbian*, with its market share of more than 60 percent, clearly dominated the smartphone industry (Müller 2007, p. 4), while *Palm* entered into financial trouble in 2007 due to declining sales figures (Hillenbrand & Müller 2007, p. 5).

B.3 The post-iPhone era: 2007 - 2011

2007 was a landmark year for the mobile communication industry. *Apple*'s announcement of the first *iPhone* in January (Apple 2007a) and the launch of the product in June (Apple 2007b) attracted enormous media attention and pushed the smartphone technology forward in terms of functionality and user-friendliness. While the majority of features on this smartphone were not completely new, the phone's most important aspects were the new user-friendly touchscreen interface, a consistently good user experience and the tight integration of the device into *Apple*'s already existing *iTunes* store for audio and video content. From this point forward, users could buy and synchronize multimedia files from their computer to their *iPhone* and use it as a multimedia player and communication device. The proprietary operating system *iPhone OS*, renamed to *iOS* in June 2010, provided the basis for this functionality. In terms of distribution strategy, *Apple* partnered with mobile operators as exclusive sales partners (e.g., *AT&T* in the USA, *T-Mobile* in Germany, *o2* in the UK) and tied the sale of the device to expensive data tariffs, thus targeting the premium market segment.

The markets reacted strongly to the success of the *iPhone* (Apple 2007c) and competitors were pressured to catch up with what was perceived as the benchmark device for the whole industry. The internet company *Google* responded by launching the *Android* smartphone platform (Google 2007) at the end of 2007. The platform was accompanied by an industry consortium, the *Open Handset Alliance*, which consisted of "a multinational alliance of technology and mobile industry leaders" (Google 2007). The *Open Handset Alliance* (OHA) initially comprised 34 partners including network operators, device manufacturers, chip makers, software companies and others who cooperated to provide a royalty-free, open-source smartphone platform. Google's own intentions with this for-free approach were twofold. Andy Rubin, a former Microsoft employee, co-founder of *Android* and Head of Mobile Platforms at *Google* described the situation as follows: "Unless there is a vendor-independent software solution, the consumer isn't going to be well served. … What android is doing is trying to avoid what happened in the PC business, which was to create a monopoly" (cited in: Auletta 2009, p. 208).[178] However, the major reason for *Google*'s engagement in the smartphone industry was said to be data collection and advertising: "smartphones will yield more data for Google. And they will allow Google to explore ads and services to generate revenues. … To protect its business interests, Google had to be in the smartphone business" (Auletta 2009, p. 266/356).

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178 Network operators such as *Verizon* saw this development in a critical light, as noted by its CEO Ivan Seidenberg: "Google's vision of Android is Microsoft's vision of owning the operating system in every PC" (cited in: Auletta 2009, p. 266).

Many network operators, device manufacturers and software firms joined the OHA to support the *Android* platform. Stock markets responded favorably to these announcements, since it strengthened the alliance members' positions on the market (Ohler et al. 2007, p. 4). Yet *Nokia*, *Symbian*'s biggest contributor and benefactor, did not perceive the *Open Handset Alliance* as a threat at that time, and *Symbian* CEO Nigel Clifford was convinced that "we are market leader and will continue to be market leader" (cited in: Ohler et al. 2007, p. 4, translation by the author). In order to strengthen its platform's position, *Microsoft* purchased the smartphone software company *Danger Inc.* in February 2008 (Markoff 2008a, p. 9). In an effort to gain greater foothold in the market, *Sony Ericsson* broadened its offers and for the first time announced a *Windows Mobile*-based device in 2008. This was interpreted as a sign of weakening of the *Symbian* platform (Müller & Lambrecht 2008, p. 4). *Palm* was also in a critical position: since it was not a member of any strategic alliance, it found itself faced with even stronger competition and experienced an existential threat (Laube & Müller 2007, p. 4).

Understanding the importance of apps for smartphones, *Google* announced the *Android Developer Challenge* at the end of 2007 with the aim of providing awards for software applications built on the *Android* platform. This was a strategic move to ensure a broad range of compatible applications even before *Android* devices became available on the market. *Google* spent a total of 10 million U.S. dollars to gain developers' attention and awarded the money to the 50 best entries. In March 2008, *Apple* opened its *iPhone* device to third-party software developers, likewise adopting the view that "software is growing in importance" (Shannon 2008, p. 7). *Apple*, which initially had not allowed third-party software to be installed on their *iPhone*, introduced the *Apple App Store* together with the second generation *iPhone* (Apple 2008b). The application store was embedded into the *iTunes* environment and was launched with 500 apps in mid-2008. This was a clear indication of the importance that smartphone software had gained over time.

Recognizing the increased role of platforms, market leader *Nokia* made a strategic decision. In June 2008, the company acquired the remaining shares of *Symbian Limited* and founded the non-profit *Symbian Foundation* (Wray 2008). With this move, the proprietary *Symbian OS* was turned into an open-source platform (Müller 2008, p. 4). Very much like *Google Android*, the platform was supported by several companies that partnered up in the newly created *Symbian Foundation*, a strategic alliance with goals congruent to its competitor, the *Open Handset Alliance*. "Nokia is already reacting to Android without even knowing its market success" concluded industry analyst Gartner in 2008 (Müller 2008, p. 4, translation by the author). In an attempt to prevent the *Android* platform and *Apple* from reducing *Nokia*'s 60 percent market share, the company not only invested substantial financial (€264 million) and human (more than 1,600 staff) resources into the *Symbian Foundation*, but also forewent substantial revenues from licensing fees by making the software code available for free to all alliance members. The alliance surrounding the platform lowered the barriers for firms to use the *Symbian* operating system, with *Nokia*'s Vice president for Symbian development Kai Öistämö commenting: "I am convinced that this will lead us to sell more phones" (Wray 2008, p. 24). Market analyst *Global Insight* characterized the situation as follows: "By tying up the top five mobile handset makers, key chipmakers and the likes of AT&T and Vodafone, Nokia wants to starve Android, and similar initiatives, of influential industry players, leaving them to toy around with smaller players with lesser chance of changing the status quo" (cited in: Wray 2008). Behind the scenes, a fierce platform competition ensued and also engulfed technology firms including various semiconductor firms and the chipmakers *Intel*, *Qualcomm* and *ARM* (Markoff 2008b, p. 1).

Despite the new alliances formed by *Google* and *Nokia*, *Apple*'s strategy with the *App Store* paid off. The firm announced the download of 10 million apps on only the first weekend of its launch, which had exceeded all expectations (Apple 2008c). With app usage increasing exponentially, industry observers concluded that the introduction of the *iPhone* in 2007 had "changed the smartphone market for ever" (Fry 2008, p. 108), not least through the inauguration of the *App Store*, which serves as a new archetype for forums where consumer demands and developers´ software meet. The ability to run applications on mobile phones was not in itself an innovation, as it had already been possible for several years on phones with the *Symbian* or *Microsoft Windows Mobile* operating systems. It was the *iPhone*, however, that brought this market to the industry's attention (Holson & Helft 2008, p. 1). When *Google* launched the first *Android* device *HTC Dream* in October 2008, the *Android Market* app store was a standard feature of the platform (Laube & Maatz 2008, p. 4). While *Apple*'s success continued and made it the second largest manufacturer in terms of sales in 2008, other manufacturers, most importantly *Palm*, *RIM*, former U.S. market leader *Motorola* and even global market leader *Nokia*, struggled with the new competition, particularly in terms of technical capabilities and design (Wendel 2008, p. 4). The concept of apps, however, was becoming universally successful across all platforms. When *Palm* launched its new *Palm Pre* handset with its own proprietary operating system *WebOS* in 2009 (Ritchel 2009, p. 4), it took only 20 days until the users of the 150,000 phones that were sold reached one million app downloads — with only 30 apps available (Wortham 2009, p. 5).

At trade fairs, such as the Mobile World Congress 2009 in Barcelona, the "battle royale" (Espiner 2008) between the platforms gained new speed as many new devices were announced (O'Brien 2009, p. 5). Platform alliances enticed new members, such as PC firms *Dell*, *Acer* and *Asus*, to enter the smartphone market (Vance 2009, p. 1). Following *Google*'s and *Apple*'s example, virtually every platform now had its own central app store (InformationWeek 2009). Despite more firms supporting the *Symbian Foundation*, the established player *Nokia* struggled severely with technological difficulties and declining sales (Maatz 2009, p. 8). The company forged new partnerships to maintain its position, for instance with *Microsoft* to integrate *MS Office*. *Apple*, the initiator of the new smartphone market, saw its technological leadership decline slowly mainly due to competition from *Android* devices. While *iPhone* sales remained strong, *Apple* saw lower growth than its major competitor. By the end of 2009, the market looked favorable for the *Android* platform (Nuttal 2009, p. 7). This had positive effects for *OHA* members such as *Motorola*, which was one of the first to fully take sides and limited itself exclusively to the *Android* platform (Hansell 2009, p. 8). With this move, the company successfully escaped from its own corporate crisis and averted bankruptcy. Despite this development and its strong involvement with the *Android* platform, *Samsung* launched its own proprietary mobile operating system called *Bada* in late 2009 (Samsung 2009). *Bada* was similar to the existing platforms in many respects, but was exclusively limited to *Samsung* devices. Hence, because of its comparatively limited user numbers, its market share remained rather low.

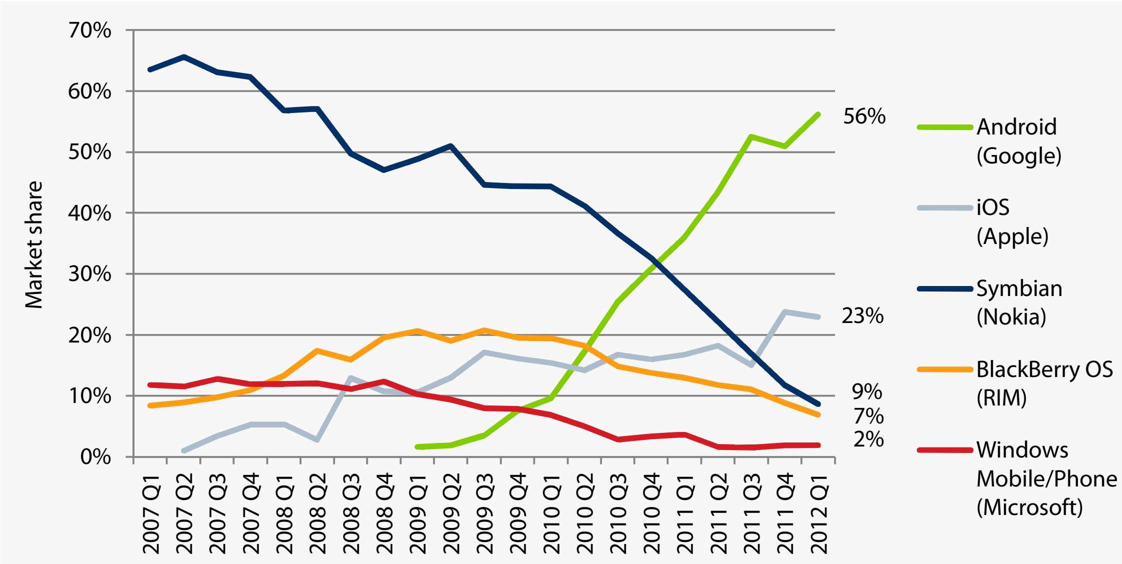
For the smartphone industry, the year 2010 began with several major announcements. Not only did *Apple*'s app store exceeded 3 billion downloads (Apple 2010a) in January, but the introduction of the *iPad* tablet computer beat the competition to the market and extended the use of *Apple*'s *iOS* platform beyond the *iPhone* and the *iPod touch*. *Google* launched its first self-branded smartphone, the *Nexus One*, and the *Android* platform found widespread usage in new smartphones and tablets computers. For *Google*, the mobile business had increased in importance to such a degree that its CEO Eric Schmidt announced the company's "mobile first" strategy at the Mobile World Congress in Barcelona (Schmidt 2010). At the same time, *Nokia*'s director of the mobile phone division Rick Simonson and other industry experts were convinced that not many ecosystems could survive in the long run (Wendel 2010a, p. 1), expecting further concentration in the industry. *Nokia* reduced their support for the *Symbian* platform in relative terms by investmenting into other ventures such as *MeeGo*, a joint operating system project with the chipmaker *Intel.*

At the *Mobile World Congress 2010*, all players were clearly focused on platforms and apps (Glahn 2010). Microsoft launched its newly designed *Windows Phone 7* operating system, the successor to the older *Windows Mobile,* which had been continuously losing ground since 2008 due to its technical inferiority. Several companies partnered up with *Microsoft* and announced new devices based on the new platform (McDougall 2010, p. 17). Most firms were faced with stagnating sales and dropping revenues as a result of the financial crisis. The struggling industry players began suing each other for patent breaches and attempted to outo each other with new product announcements. In order to gain a foothold in the smartphone market, *Hewlett-Packard* purchased *Palm* including its *WebOS* platform in mid-year 2010 (Vance & Wortham 2010, p. 1). Shortly after this announcement, it became clear that the *Android* platform would be the largest benefactor of the 72-percent market growth (Wray 2010, p. 27). *Nokia*'s immediate response to this trend and its corresponding 40-percent sales decline was a corporate restructuring. The company formed a new division dedicated entirely to smartphones, changed top executives and cut jobs (Ward & Parker 2010, p. 2; Wendel 2010b, p. 2). At the end of the year, *Sony Ericsson* and *Samsung* announced that they would no longer support the *Symbian Foundation,* but rather switch to *Android* for new products (Ohler 2010, p. 1). This announcement marked a turning point for *Symbian.* Even though many smaller companies still relied on this strategic alliance, *Nokia* remained the only large manufacturer with an interest in the *Symbian* operating system. With e-books and mobile music streaming, new types of digital content were entering the smartphone realm and immediately achieved strong sales (Charles Arthur 2010, p. 5). *Google*'s announcement of its newest self-branded smartphone *Nexus S* at the end of 2010 not only demonstrated their technical prowess but also the market momentum of the *Android* platform, which by the end of the year 2010 had outsold all other competing platforms, not only with smartphones but also increasingly with tablet computers.

Just as in the years before, the *Mobile World Congress* 2011 in Barcelona introduced major changes to the smartphone industry. Apart from many new product introductions, probably the most important announcement of the year came from market leader *Nokia*. Faced with continuous market share losses, *Nokia*'s CEO Stephen Elop used strong words to describe *Nokia*'s miserable situation in the smartphone industry: "We are standing on a burning platform" (Elop 2011). By this, Elop was referring to the fierce competition from *Apple* and *Google* which had caused *Nokia*'s drop in market share. The phone business had become a software business, and Nokia had failed to establish a successful ecosystem around its *Symbian OS*: "The battle of devices has now become a war of ecosystems, where ecosystems include not only the hardware and software of the device, but developers, applications, … and many other things. Our competitors aren't taking our market share with devices; they are taking our market share with an entire ecosystem" (Elop 2011). After several rumors and days of speculation, the industry was convinced that "Nokia [was] at the crossroads" (Economist 2011a). The big change was announced only days later: *Nokia* was quitting *Symbian* and partnering with *Microsoft* for its new smartphones in order to "compete in the war of ecosystems" (Elop 2011). Industry experts such as *IDC* summarized the move as follows: "It's Nokia going for the best option that was available to it. It remains to be seen whether it will work or not" (cited in: Charles Arthur 2011, p. 42). Other industry experts were skeptical that "two wrongs could make a right" (Noyes 2011). *RIM*, once a forerunner in the industry with its messaging-oriented *BlackBerry* smartphones, was also struggling and was facing an uncertain future (Lambrecht 2011; Simon & Taylor 2012).

To summarize the fierce platform competition in the smartphone industry, Figure Figure B-3 shows the quarterly market shares of the major smartphone platforms between 2007 and the first quarter of 2012.

Figure B-3 **Market shares of major smartphone platforms 2007-2012**
(Data source: Gartner 2008a, 2008b, 2008c, 2009, 2010c, 2010d, 2010e, 2011b, 2011c, 2011d, 2011e, 2012a; 2012b; own calculations)



As of the beginning of 2012, *Apple* and *Google*, two players with very different strategies, currenty dominate the smartphone industry.

Apple is a prime example of a closed, tightly-controlled ecosystem. *Apple*'s operating system is a proprietary, closed-source development, available exclusively on *Apple* devices. Apps are distributed *only* through its own *App Store* with *Apple* earning a 30-percent commission on every software application sold. Developers must get their apps approved by *Apple*, which claims that this process ensures a better user experience. However, the company has been accused of misuse of power by banning apps that could impair *Apple's* business objectives (Johnson & Schatz 2009). Compared to the situation in the PC industry, this is a revolutionary shift in power. An analogy to the PC market would be *Microsoft* exclusively controlling the software distribution for *Windows* PCs, censoring all software applications and taking a 30-percent share from the developers. In early 2010, *Apple* tried to lock in developers to their *iPhone* platform by legally excluding other programming languages and/or cross-compilers. With this, market leader *Apple* was intentionally hampering the portability of apps to other smartphone platforms, making multi-homing more difficult (McAllister 2010). In the face of fierce opposition, *Apple* later relaxed these restrictions (Apple 2010b).

Apart from their apps strategy, the company also limits the kind of content that can be offered, for instance prohibiting 'explicit and offensive material', which is determined according to their *own* definition (Apple 2011a; Spiegel 2010). Furthermore, *Apple* also earns a 30-percent share of any digital media sales offered by third-party publishers, such as e-books, newspaper subscriptions or music offered by third-party publishers (Economist 2011b). Publishers are "not permitted to offer cheaper deals outside Apple's walled garden" (Halliday 2011). These business practices have led to strong opposition from publishers, who refuse to relinquish too much control and money to *Apple* (Economist 2011b).

Google follows a more open approach. Its open-source operating system is developed in cooperation with other industry partners and is available on a wide range of devices from different handset makers. *Google's Android Market* is similar to *Apple*'s distribution platform, also charging a 30-percent commission for any app purchased. However, *Google* allows for alternative distribution channels on A*ndroid* devices and is less strict with regard to censorship (Kendrick 2011). In February 2011, the company announced *Google One Pass*, a distribution platform for digital content across websites and mobile apps. Unlike Apple's offer, Google will take a 10-percent commission from publishers, as well as giving them freedom on pricing decisions and providing access to customer data (Bradshaw & Gelles 2011). However, the company has also been subject to legal disputes regarding privacy and data protection issues with their *Android* platform (Financial Times Deutschland 2011).

Despite the success of *Apple* and *Google,* the rise of smartphones has brought trouble to other companies. Various electronic devices are now commonly integrated into smartphones, and "there is no doubt that the smartphone is transforming many of these markets, not just navigation devices, but cameras and media players" (O'Brien 2010). Makers of dedicated navigation devices, such as *Garmin* or *TomTom*, are struggling to compete with smartphone-based navigation solutions from *Google* or *Nokia*, which provide their service free of charge (Wolde 2010). With the miniaturization of camera lenses and sensors improving at rapid speed, smartphones are eroding sales of lower-end digital cameras. Indeed, *Nokia* was reported to be the world's largest manufacturer of digital cameras in 2010 (O'Brien 2010). In the handheld digital games industry, estimated at 25 billion U.S. dollars a year, smartphones are undermining the traditional duopoly of *Sony* and *Nintendo* (Economist 2011c), because smartphone devices are now powerful enough for sophisticated gaming. Accordingly, *Apple's* and *Google's* smartphone platforms together were estimated to account for 34 percent of the U.S. portable game software revenues in 2010 (Dredge 2011). Smartphones have also targeted the electronic payment market. For instance, *Google* has partnered with *MasterCard* and *Citigroup* to develop a new mobile payment system which will allow smartphone owners to make purchases based on 'near field communication' (NFC) technology built into modern smartphones (Efrati & Sidel 2011). Summarizing these examples, Auletta (2009, p. 302) stresses the universal importance of smartphones as converged devices: "Your phone will replace your credit card, your keys. It will become your personal remote control to life." As a result, smartphones are transforming the competitive landscape in a wide range of industries with strong economic implications.

For network operators, smartphones are both a blessing and a curse. Due to fierce price competition, the Average Revenue per User (ARPU) has been declining for several years (ABIresearch 2010).[179] While increased mobile data usage caused largely by smartphones helps network operators to recover lost revenues (EITO 2009), the increased data usage also poses challenges for operators, since their networks have already been breaking down under the higher traffic (Rysavy 2009, p. 23). Their reaction of restricting the data throughput and thus usability for certain applications such as video streaming or voice-over-IP services (Cohn 2010) has garnered operators much criticism in the so-called net neutrality debate, which now also extends to the landline networks and internet access (European Commission 2011).

Apart from these developments, smartphones have also been responsible for a shift in power from network operators to platform providers. By signing exclusive distribution deals for the early *iPhone* generations, *Apple* was able to negotiate substantial revenue shares from network operators. For instance, in 2007 the British network operator *O2* was rumored to "return to Apple as much as 40% of any revenues it makes from customers' use of the device" (Wray 2007). Similar deals had never before been seen in the industry. To summarize, while the introduction of smartphones provides new revenue opportunities for operators, it has significantly changed the traditional industry structure through power shifts and new industry alliances. Together with new bandwidth demands by users, smartphones thus also presents new challenges for network operators.

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179 In the European Union, the fierce price competition among standardized and comparable call and text message services has been reinforced by regulation from the European Commission. The Commission repeatedly limited the EU internal roaming fees and the national call and SMS rates that operators can charge their customers. These steps were taken in order to drive down price levels set by former national monopolists and to enable customers to profit from the efficiency gains of increasingly global companies (European Commission 2008, 2009, 2010).

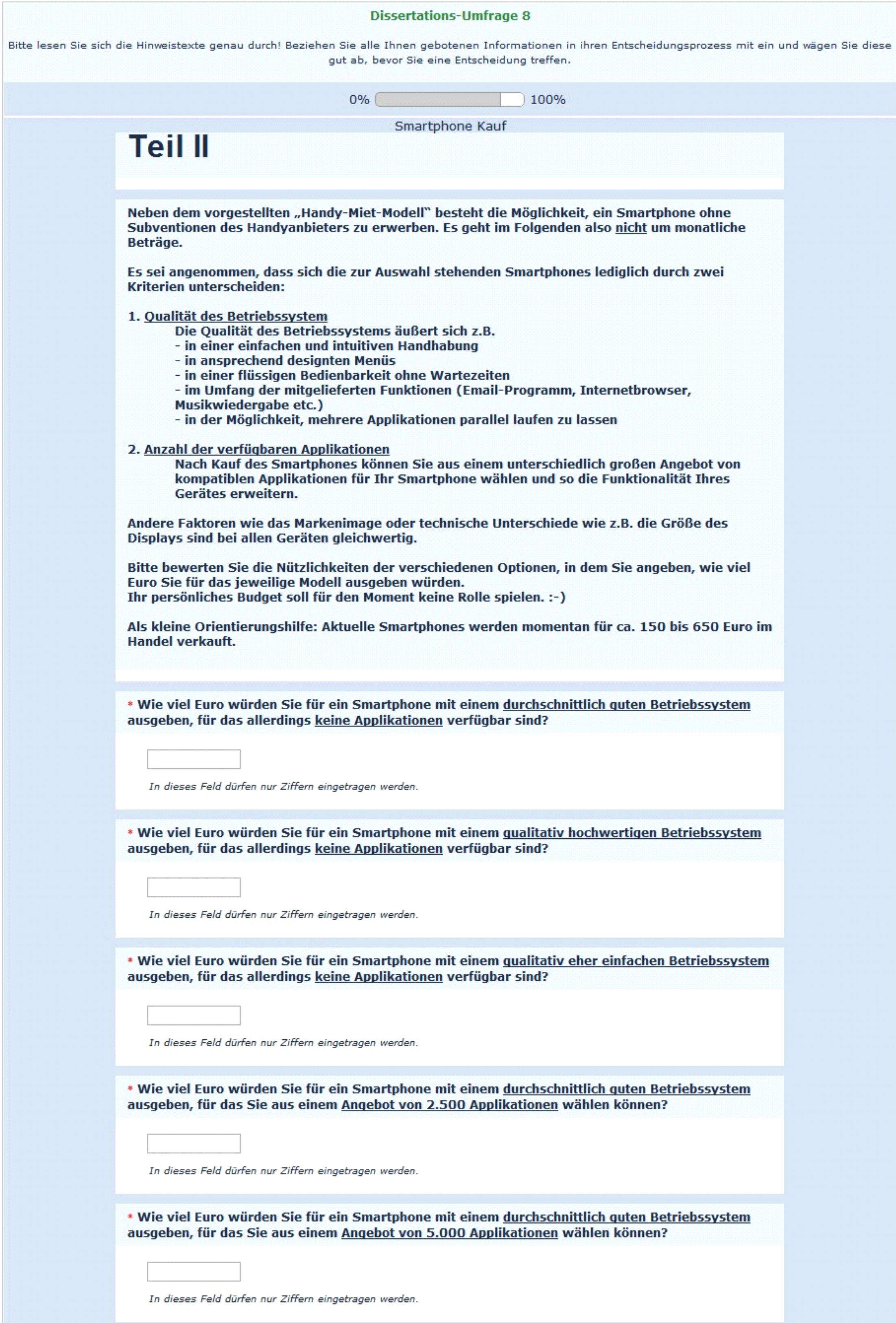
The success of smartphones has not come without public debate on their social implications. Smartphones are highly influential in people's daily life because they have lead to what has been called an 'always-on culture', i.e., a society with constant internet connectivity (Völker 2010, p. 30). At the individual level, this permanent internet access can lead to an information overload or "data addiction" in which users seek constant "digital stimulation" (Grossman 2007) by checking emails, news or instant messaging. Furthermore, the constant connectedness leads to a blurring of boundaries between people's professional and private lives.

From a societal perspective, smartphones have a profound impact on media and democracy. With their many functions, smartphones can record and instantly distribute photos and video content, thus turning their users into *citizen reporters*. In that sense smartphones, through their sheer technical capabilities, have become "a catalyst for democracy" (Bleich & Kuri 2011, p. 86, translation by the author).

On the other hand, this innovative technology has provoked serious privacy and data protection concerns. Smartphones rely on detailed positioning data for many services, such as location-based search results, price comparison in local shops and satellite navigation for automobiles, bicycles and pedestrians. For advertisers and businesses alike, location is where the money is, and smartphones gather a large amount of data about their users (Carr 2010, p. 1). As a consequence, smartphones are redefining the role that advertising plays in the society. By combining location data, shopping preferences and internet search behavior, advertising can be tailored to people's social context: "our physical location, social contacts and preferences shape the information we receive. … 'Context' has now become just as important as 'content'" (Grech 2011). In particular, search providers such as *Google* and *Microsoft* collect location data together with the search terms or online activity of users. On the one hand, this allows advertising to be more relevant to users. However, the resulting "end of privacy" (von Bredow et al. 2010, pp. 58-69) is considered problematic, and users are taking legal action to defend themselves against the data being gathered about them and their location (Gaschke 2010). Others, especially younger people, seem to be less concerned regarding the use of their data: "For many, the benefits of augmented reality outweigh issues of privacy" (Carr 2010). In this sense "privacy may turn out to have become an anomaly" (Markoff 2008c).

* * *

Appendix C Screenshots of the consumer survey


Dissertations-Umfrage 8

Bitte lesen Sie sich die Hinweistexte genau durch! Beziehen Sie alle Ihnen gebotenen Informationen in ihren Entscheidungsprozess mit ein und wägen Sie diese gut ab, bevor Sie eine Entscheidung treffen.

0% 100%

Smartphone Kauf

Teil II

Neben dem vorgestellten „Handy-Miet-Modell" besteht die Möglichkeit, ein Smartphone ohne Subventionen des Handyanbieters zu erwerben. Es geht im Folgenden also nicht um monatliche Beträge.

Es sei angenommen, dass sich die zur Auswahl stehenden Smartphones lediglich durch zwei Kriterien unterscheiden:

1. Qualität des Betriebssystem
Die Qualität des Betriebssystems äußert sich z.B.
- in einer einfachen und intuitiven Handhabung
- in ansprechend designten Menüs
- in einer flüssigen Bedienbarkeit ohne Wartezeiten
- im Umfang der mitgelieferten Funktionen (Email-Programm, Internetbrowser, Musikwiedergabe etc.)
- in der Möglichkeit, mehrere Applikationen parallel laufen zu lassen

2. Anzahl der verfügbaren Applikationen
Nach Kauf des Smartphones können Sie aus einem unterschiedlich großen Angebot von kompatiblen Applikationen für Ihr Smartphone wählen und so die Funktionalität Ihres Gerätes erweitern.

Andere Faktoren wie das Markenimage oder technische Unterschiede wie z.B. die Größe des Displays sind bei allen Geräten gleichwertig.

Bitte bewerten Sie die Nützlichkeiten der verschiedenen Optionen, in dem Sie angeben, wie viel Euro Sie für das jeweilige Modell ausgeben würden.
Ihr persönliches Budget soll für den Moment keine Rolle spielen. :-)

Als kleine Orientierungshilfe: Aktuelle Smartphones werden momentan für ca. 150 bis 650 Euro im Handel verkauft.

* **Wie viel Euro würden Sie für ein Smartphone mit einem durchschnittlich guten Betriebssystem ausgeben, für das allerdings keine Applikationen verfügbar sind?**

In dieses Feld dürfen nur Ziffern eingetragen werden.

* **Wie viel Euro würden Sie für ein Smartphone mit einem qualitativ hochwertigen Betriebssystem ausgeben, für das allerdings keine Applikationen verfügbar sind?**

In dieses Feld dürfen nur Ziffern eingetragen werden.

* **Wie viel Euro würden Sie für ein Smartphone mit einem qualitativ eher einfachen Betriebssystem ausgeben, für das allerdings keine Applikationen verfügbar sind?**

In dieses Feld dürfen nur Ziffern eingetragen werden.

* **Wie viel Euro würden Sie für ein Smartphone mit einem durchschnittlich guten Betriebssystem ausgeben, für das Sie aus einem Angebot von 2.500 Applikationen wählen können?**

In dieses Feld dürfen nur Ziffern eingetragen werden.

* **Wie viel Euro würden Sie für ein Smartphone mit einem durchschnittlich guten Betriebssystem ausgeben, für das Sie aus einem Angebot von 5.000 Applikationen wählen können?**

In dieses Feld dürfen nur Ziffern eingetragen werden.

* **Wie viel Euro würden Sie für ein Smartphone mit einem durchschnittlich guten Betriebssystem ausgeben, für das Sie aus einem Angebot von 10.000 Applikationen wählen können?**

In dieses Feld dürfen nur Ziffern eingetragen werden.

* **Wie viel Euro würden Sie für ein Smartphone mit einem durchschnittlich gutem Betriebssystem ausgeben, für das Sie aus einem Angebot von 50.000 Applikationen wählen können?**

In dieses Feld dürfen nur Ziffern eingetragen werden.

* **Wie viel Euro würden Sie für ein Smartphone mit einem qualitativ hochwertigen Betriebssystem ausgeben, für das Sie aus einem Angebot von 2.500 Applikationen wählen können?**

In dieses Feld dürfen nur Ziffern eingetragen werden.

* **Wie viel Euro würden Sie für ein Smartphone mit einem qualitativ hochwertigen Betriebssystem ausgeben, für das Sie aus einem Angebot von 5.000 Applikationen wählen können?**

In dieses Feld dürfen nur Ziffern eingetragen werden.

* **Wie viel Euro würden Sie für ein Smartphone mit einem qualitativ hochwertigen Betriebssystem ausgeben, für das Sie aus einem Angebot von 10.000 Applikationen wählen können?**

In dieses Feld dürfen nur Ziffern eingetragen werden.

* **Wie viel Euro würden Sie für ein Smartphone mit einem qualitativ hochwertigen Betriebssystem ausgeben, für das Sie aus einem Angebot von 50.000 Applikationen wählen können?**

In dieses Feld dürfen nur Ziffern eingetragen werden.

* **Wie viel Euro würden Sie für ein Smartphone mit einem qualitativ eher einfachen Betriebssystem ausgeben, für das Sie aus einem Angebot von 2.500 Applikationen wählen können?**

In dieses Feld dürfen nur Ziffern eingetragen werden.

* **Wie viel Euro würden Sie für ein Smartphone mit einem qualitativ eher einfachen Betriebssystem ausgeben, für das Sie aus einem Angebot von 5.000 Applikationen wählen können?**

In dieses Feld dürfen nur Ziffern eingetragen werden.

* **Wie viel Euro würden Sie für ein Smartphone mit einem qualitativ eher einfachen Betriebssystem ausgeben, für das Sie aus einem Angebot von 10.000 Applikationen wählen können?**

In dieses Feld dürfen nur Ziffern eingetragen werden.

* **Wie viel Euro würden Sie für ein Smartphone mit einem qualitativ eher einfachen Betriebssystem ausgeben, für das Sie aus einem Angebot von 50.000 Applikationen wählen können?**

In dieses Feld dürfen nur Ziffern eingetragen werden.

Weiter >>

[Umfrage verlassen und löschen]

Dissertations-Umfrage 8

Bitte lesen Sie sich die Hinweistexte genau durch! Beziehen Sie alle Ihnen gebotenen Informationen in ihren Entscheidungsprozess mit ein und wägen Sie diese gut ab, bevor Sie eine Entscheidung treffen.

0% 100%

Abschluß

***Zum Abschluß noch ein paar allgemeine Fragen.**

Besitzen Sie selber ein Smartphone?

(•) Ja ( ) Nein

***Würden Sie Ihr Smartphone im Allgemeinen weiterempfehlen?**

( ) Ja ( ) Nein

***Mit welchem Betriebssystem ist Ihr Smartphone ausgestattet?**

Bitte wählen Sie eine der folgenden Antworten.

Bitte wählen...

***Haben Sie beim Kauf, abgesehen von Ihrem Smartphone, weitere Geräte mit anderen Betriebssystemen in die engere Auswahl gezogen?**

(•) Ja ( ) Nein

***Bitte wählen Sie aus, welche Plattformen Sie ebenfalls in die engere Auswahl gezogen haben**

Bitte wählen Sie einen oder mehrere Punkte aus der Liste aus.

- [ ] Apple iPhone iOS
- [ ] Google Android
- [ ] Symbian OS
- [ ] Windows Mobile
- [ ] BlackBerry OS
- [ ] Sonstiges Betriebssystem

***Mit wie vielen Personen aus Ihrem persönlichen Umfeld haben Sie ungefähr über die Wahl des Smartphones gesprochen, bevor Sie sich für ein Modell entschieden haben?**

In dieses Feld dürfen nur Ziffern eingetragen werden.

***Wie hoch ist ihre durchschnittliche monatliche Handyrechnung?**

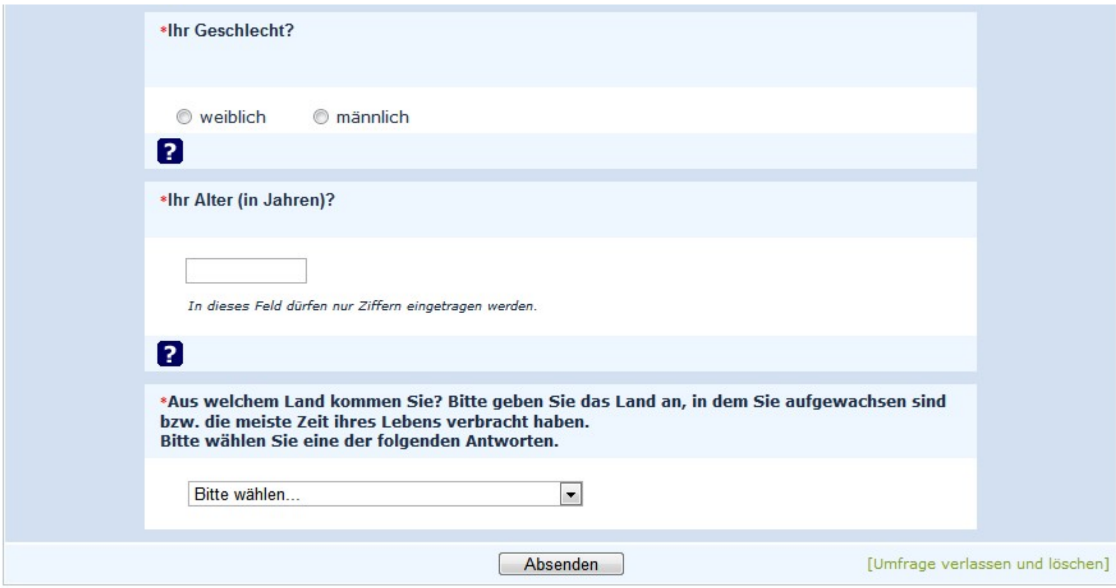
In dieses Feld dürfen nur Ziffern eingetragen werden.

***Wie stark bzw. schwach ist Ihr Interesse für technische Produkte allgemein? Bitte beurteilen Sie anhand der vorgegebenen Skala:**

	sehr stark 1	2	3	4	relativ stark 5	6	7	8	weder noch 9	10	11	12	relativ schwach 13	14	15	16	sehr schwach 17
Mein Technikinteresse ist...	( )	( )	( )	( )	( )	( )	( )	( )	( )	( )	( )	( )	( )	( )	( )	( )	( )

***Bitte geben Sie für die nachfolgenden Aussagen an, inwieweit diese auf Sie selber zutreffen.**

	trifft nicht zu (1)	trifft überwiegend nicht zu (2)	trifft eher nicht zu (3)	weder noch (4)	trifft eher zu (5)	trifft überwiegend zu (6)	trifft zu (7)
Meine Meinung zu Smartphones scheint bei anderen Leuten nicht zu zählen.							
Freunde und Bekannte wenden sich mit Fragen eher an andere Personen als an mich, bevor sie ein Smartphone kaufen.							
Andere Leute bitten mich um Rat bei ihrer Entscheidung für ein bestimmtes Smartphone.							
Menschen aus meinem persönlichen Umfeld wählen Smartphones auf Basis meiner Empfehlung.							
Häufig überzeuge ich andere Leute das Smartphone-Modell zu kaufen, das ich selbst für gut halte.							
Ich beeinflusse oft die Meinung anderer Leute zu Smartphones.							
Wenn ich erwäge ein Smartphone zu kaufen frage ich andere Leute um Rat.							
Ich brauche den Rat anderen Leuten nicht, wenn ich ein Smartphone kaufe.							
Ich frage selten andere Leute, welches Smartphone ich kaufen sollte.							
Ich verlasse mich oft auf die Meinung meiner Freunde und Bekannte, bevor ich mich für ein bestimmtes Smartphone entscheide.							
Ich fühle mich viel sicherer beim Kauf eines Smartphones wenn ich vorher die Meinung anderer Leute eingeholt habe.							
Bei der Wahl eines Smartphones spielt die Meinung anderer Leute für mich gar keine Rolle.							


*Ihr Geschlecht?
weiblich
männlich
?
*Ihr Alter (in Jahren)?
In dieses Feld dürfen nur Ziffern eingetragen werden.
?
*Aus welchem Land kommen Sie? Bitte geben Sie das Land an, in dem Sie aufgewachsen sind bzw. die meiste Zeit ihres Lebens verbracht haben.
Bitte wählen Sie eine der folgenden Antworten.
Bitte wählen...
Absenden
[Umfrage verlassen und löschen]

Appendix D Guideline for interviews with developers

[Offene Einstiegsfrage] *„Seit wann beschäftigen Sie sich mit der Smartphone-Industrie? Welche Funktion üben Sie im Unternehmen aus? Wann haben Sie mit der Entwicklung von Apps begonnen?“*

Auswahl der Plattformen *„Wie wurde damals die Entscheidung getroffen, für welche technologische(n) Plattform(en) entwickelt werden soll?“*
Zufällige Entscheidung oder bewusste Abwägung der Alternativen? Kriterien? Falls extern vorgegeben: (vermutete) Kriterien des Auftraggebers? Beispiele: „Marktführer“, „60/80/100% des Marktes abdecken“, „die größten 2/3 Plattformen“, „Marktanteil > x%“, „beste Technologie“, „lukrativste Zielgruppe“, „Sympathie für bestimmte Plattformen“, „passt zu Vorkenntnissen“ (Programmiersprachen) Falls Marktanteile: Quartals- oder 12-Monats-Zahlen? Installed base? Aktuelle / erwartete Marktanteile? Erwartungsbildung? Quellen? Zeithorizont?

Wechsel der Plattformen *„Wie häufig wird die Auswahl der unterstützten Plattform(en) überdacht?“*
Beispiele: „permanenter Prozess“, „wenn neue Marktanteile publiziert werden“, „bei neuen Aufträgen“ Wie lange dauert die Einarbeitung in eine neue Technologie? Signifikant? Kosten, die bei einem Wechsel entstehen? Obsoletes Fachwissen / Mitarbeiter?

Single-Homing / Multi-Homing *„Welche Vor- und Nachteile sind damit verbunden, parallel für mehrere Plattformen zu entwickeln?“*
Beispiele Vorteile: Größeres Marktpotential für Apps, Risikominimierung, Portierung bringt Synergien (Ideen, Code, Grafiken, Daten, Backend) Beispiele Nachteile: erhöhter Zeitaufwand für Weiterbildung / Kosten für Geräte zum Testen / Support Wie würden Sie die Synergien quantifizieren? Wie viel % der Arbeit kann etwa erneut genutzt, wenn eine Applikation auf andere Plattformen portiert wird?

Zukunftsperspektive *„Wie sieht Ihrer Meinung nach die Smartphone-Landschaft der Zukunft aus? Wie viele Plattformen werden langfristig bestehen bleiben?“*
Welche? Und warum? Vergleich mit Desktop-Markt: Welche Parallelen und Unterschiede existieren Ihrer Meinung nach?

Appendix E Abstract

Abstract

This dissertation proposes an agent-based simulation model of platform competition to investigate the phenomenon of technological path dependence in two-sided markets. The computer simulation explores the interaction of indirect network effects, bounded rationality, switching behavior, multi-homing strategies and entry timing of competing technologies. The study illustrates different market dynamics by conducting counterfactual experiments for the global smartphone industry, and identifies conditions which are (un)favorable to the emergence of technological lock-ins. On these grounds, the dissertation contributes to the theoretical literature on path dependence by complementing existing empirical case studies with a formal simulation model.

Kurzfassung

Im Rahmen der Dissertation wird ein agentenbasiertes Simulationsmodell entwickelt, dass die Entstehung technologischer Pfadabhängigkeiten in zweiseitigen Märkten untersucht. Die Computersimulation erforscht die Interaktion von indirekten Netzeffekten, begrenzter Rationalität, Wechselverhalten, ‘multi-homing’ Strategien und dem Markteintrittszeitpunkt konkurrierender Technologien. Die Arbeit illustriert unterschiedliche Wettbewerbsdynamiken mit Hilfe von kontrafaktischen Experimenten für die globale Smartphone-Industrie. Auf dieser Grundlage werden (nicht-)förderliche Faktoren für die Entstehung von technologischen Lock-ins identifiziert. Das formale Simulationsmodell ergänzt bestehende empirische Fallstudien zu technologischen Pfaden und liefert damit einen theoretischen Beitrag zur Pfadabhängigkeitsforschung.

Appendix F Co-authorship and publications

Co-authorship

The description of the empirical case (chapter 6 and appendix B) was written in cooperation with Frithjof Stöppler. It is the result of our joint empirical research on the smartphone industry over three years. The cooperation took place in context of the Pfadkolleg Research Center and has been approved by the supervisors.

Publications and conference papers related to the dissertation

Does quality win? A simulation study on technological path dependence in two-sided markets. Proceedings of the ANZMAC 2011 Conference, Perth (Australia), November 28-30, 2011 (with Michael Kleinaltenkamp).

Path dependence in two-sided markets. 2nd International Conference on Path Dependence, Freie Universität Berlin, Germany, March 3-4, 2011.

Inter-organizational networks and platform competition. A path dependence perspective on social capital and evidence from the smartphone operating systems market. 26th EGOS Colloquium, Sub-Theme on Imprints of the Past: Organizational Path Dependencies, Universidade Nova de Lisboa, Portugal, June 28 - July 3, 2010 (with Frithjof Stöppler).

Does the winner take it all? Technology diffusion and platform competition in the smartphone industry. International Workshop on Agent-based Simulation of Diffusion Processes, Vienna, Austria, April 8-9, 2010 (with Frithjof Stöppler).

Appendix G Curriculum vitae

For reasons of data protection, the curriculum vitae is not included in the online version of this dissertation.