Standard Diffusion in Networks: A Set of Models to Analyze IT Infrastructure Path Dependence

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Abstract

Standards enable effective collaboration among individuals, organizations, and systems of all sorts in our increasingly digitized society. Self-reinforcement in standard diffusion processes creates installed base advantages for adopters, credible standards, and fosters a variety of complementary products and services. Self-reinforcement, however, breeds path dependence and lock-in. Newly introduced, more efficient standards are often disadvantaged because they have smaller networks.

The examples of global airline distribution and organizational IT infrastructures suggest that work focusing primarily on the network size – in the tradition of Arthur's path dependence model – has difficulties explaining how inertia actually builds up and how important standardization patterns such as islands of shared technologies can arise. As the notion of path dependence has come to impact research and managerial thinking, I believe it is important to relax restrictive boundary conditions of its conceptual core. I contend that path dependence theory must account for a broader range of interaction patterns and growth logics. I view path dependence as a problem of standard diffusion in networks.

Consistent with this view, I first suggest a model of standard diffusion in growing networks. The model reproduces Arthur's path dependence model and a Polya Process as special cases and allows testing of the effect of different growth parameters on path building. Agent-based simulations show that network effects – formed as a function of a growing network size – and spillover effects – contingent on the degree to which an agent's partners adopt – are usefully distinguished in growing networks as having different, non-monotonic effects on diversity. Network effects foster one standard's dominance due to increasing network influences. Spillover effects, in contrast, limit influences from growing network sizes: segregated regimes can come to settle as new agents are less dependent on the total number of adopters. A case study of a recycling company demonstrates the model's usefulness for understanding the evolution of organizational IT landscapes. In addition, a method is introduced to IT managers and architects that identifies critical IT systems with respect to their architectural embeddedness and links a system's network position with continuance inertia.

Based on problems of path creation in global airline distribution IT, I then suggest a second model conceptualizing the diffusion of a new standard as a contagious process that spills over from one organization to another. I operationalize codeshare linkages among airlines as a network and perform a network analysis. External shocks potentially trigger domino effects that cascade through the network. I test scenarios with respect to varying adoption thresholds that enable me to examine when and where a new standard diffuses to a nontrivial fraction of agents. I introduce a group detection algorithm – switching maximum cliques of players – to demonstrate the effectiveness of targeted compared to random network interventions. A two-step procedure for path breaking is thus suggested that identifies a set of key players and switches them collectively.

Viewed together, these results demonstrate the value of a network perspective to understand better path dependencies in complex (inter-)organizational IT infrastructures.

Zusammenfassung

Standards unterstützen Individuen, Organisationen und Systeme verschiedener Ausprägung in einer zunehmend digitalen Gesellschaft effektiv zusammenzuarbeiten. Durch selbstverstärkende Dynamiken profitieren Nutzer verbreiteter Standards von Vorteilen: Einer größeren „Installed Base“, der Zuverlässigkeit eines etablierten Standards und der Verfügbarkeit komplementärer Produkte und Services. Selbstverstärkende Dynamiken in Standarddiffusionsprozessen gehen jedoch mit Pfadabhängigkeit und Lock-In einher. Neu eingeführte, effiziente Standards sind häufig benachteiligt, da diese auf kleinere Netzwerke zurückgreifen können.

Anhand der Beispiele von IT-Infrastrukturen im globalen Airline-Vertrieb und organisationalen IT-Architekturen wird deutlich, dass Studien die sich – wie das Pfadabhängigkeitsmodell von Brian Arthur – primär auf die Netzwerkgröße als Erklärung für Pfadbildungsprozesse beziehen, unzureichend sind. Häufig auftretende Phänomene wie Verfestigungstendenzen in Teilen eines Systems werden ausgeblendet. Aufgrund der zunehmenden Bedeutung des Pfadabhängigkeitskonzepts in Forschung und Management ist es wichtig, grundlegende Annahmen bestehender Modelle einer komplexeren Realität anzupassen und Freiheitsgrade in Bezug auf Interaktionsmuster und Wachstumslogiken zuzulassen. Diese Arbeit geht davon aus, dass Pfadabhängigkeit als Problem der Standarddiffusion in Netzwerken verstanden werden kann.

Ausgehend davon wird zunächst ein Modell der Standarddiffusion in wachsenden Netzwerken entwickelt. Das Modell reproduziert Ergebnisse des Modells von Arthur und einer Art von Polya-Prozessen als Spezialfälle und ermöglichst es den Einfluss verschiedener Wachstumsparameter auf Pfadbildungsprozesse zu untersuchen. Mittels einer agentenbasierten Simulation wird gezeigt, dass „Spillover“-Effekte – externe Einflüsse abhängig von dem Interaktionsgrad zwischen Agenten – von Netzwerkeffekten – Einflüsse abhängig von der Verbreitung des Standards im Gesamtnetzwerk – zu unterscheiden sind. Beide Einflussarten haben in wachsenden Netzwerken unterschiedliche Konsequenzen auf die Diversität im Netzwerk. Netzwerkeffekte begünstigen die Dominanz einer Lösung, da externe Einflüsse mit der Netzwerkgröße wachsen. Im Gegensatz dazu begrenzen Spillover-Effekte den Einfluss wachsender Netzwerke: In einzelnen Teilen des Netzwerks können sich lokale Standards herausbilden und verfestigen. Anhand des Falls eines Recycling-Unternehmens wird der Nutzen des Modells demonstriert, um Wachstumsprozesse innerhalb von organisationalen IT-Landschaften zu verstehen. Außerdem wird eine Methode vorgestellt, die IT-Manager und Architekten unterstützt, kritische Systeme anhand ihrer architekturelle Einbettung zu erkennen und mit dem zu erwartenden Grad der Trägheit in Verbindung zu setzen.

Basierend auf Problemen einen neuen Airline-Distributions-Standard zu etablieren, wird dann ein Modell von Standarddiffusion als Imitationsprozess zwischen miteinander interagierenden Organisationen vorgeschlagen. In dem Netzwerk sind Airlines als Knoten und Codeshare-Verbindungen als Kanten abgebildet. Eingriffe in das Netzwerk können Dominoeffekte auslösen, die sich innerhalb des Netzwerks ausbreiten. Weiterhin wird ein Algorithmus einführt, bei dem eine maximale Clique kollektiv wechselt. Diese Interventionsart

wird mit ungezielten Eingriffen verglichen. Hieraus ergibt sich eine Zwei-Schritt-Prozedur zum Pfadbruch: Die Identifikation einer Kerngruppe und deren kollektiver Wechsel.

Gesamthaft zeigen die erzielten Ergebnisse den Nutzen einer Netzwerkperspektive, um Pfadabhängigkeiten in komplexen (inter-)organisationalen IT-Infrastrukturen besser zu verstehen.

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List of Original Publications

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Fürstenau, D., Rothe, H. (2014) Shadow IT Systems: Discerning the Good and the Evil. *European Conference on Information Systems (ECIS),* Tel Aviv, 2014.

List of Abbreviations

ATPCo	Airline tariff publishing company
CRS	Computer reservation system
EDI	Electronic data interchange
ERP	Enterprise resource planning
GDS	Global distribution system
IATA	International air transport association
IS	Information system
IT	Information technology
NDC	New distribution capability
RBD	Reservation booking designator or booking class
RTDP	Real-time dynamic pricing engine
SABRE	Semi-automatic business research environment
SWISS	Swiss International Air Lines Ltd.
XML	eXtensible markup language

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Part I

The Problem of IT Infrastructure Path Dependence

What can be said at all can be said clearly; and whereof one cannot speak thereof one must be silent.

(Ludwig Wittgenstein)

Chapter 1

Introduction and Motivation

The "vicious" booking class[1] – a fifty years old technical standard in airline distribution – persists since the early days of automation. Disk space was limited then and designers of early airline reservation systems decided to restrict booking class implementation to one digit. This was sufficient for a long time and enabled a period of successful growth. Facing discontinuous change from low-cost competition with pure web distribution, airlines want, however, to go beyond just providing the price and the booking class to their customer. They want to sell individualized services, ancillaries and all kinds of extras, which they cannot do with the sales systems in place today (Isler and D'Souza 2009; Pölt 2011; Westermann 2013). Network carriers in particular – operating a long-haul network on a hub-structure – face significant inertia in displacing their booking class-based strategies.

This is one example from a class of problems of IT infrastructure path dependence. What locks an organization or even an entire industry into a 'wrong' standard? The theoretical answer is self-reinforcing mechanisms. Referring to early work on standardization, several sources of self-reinforcement have been identified: large setup or fixed costs, learning effects, coordination effects, and adaptive expectations (Arthur 1988). The underlying theoretical notion is one of network effects. The concept was applied to a variety of situations "in which the benefits of owning a product, or using a standard, or, in fact, taking any action, increased with the number of people doing the same thing" (Liebowitz and Margolis 2013:128). To explain path dependence, work on standardization has primarily focused on the network size, the number of actors using the same standard (cf. Afuah 2013; Weitzel et al. 2006).

I build a conception of path dependence that draws on these earlier lines of research but also departs from them in an important respect. While harnessing the notion of network effects, I also draw on the concepts of "interaction patterns" and "growth" as developed in works from network analysis to account for the path-dependent consequences that arise when a system grows in nontrivial ways and becomes increasingly complex. I use the term interaction patterns to refer to couplings among individual agents in a network that is not fully meshed and to describe how actions transmit by these interaction patterns, as when technological standards spill over from one organization to another. By growth, I refer to processes in which new agents entering a network will not be fully connected to all other agents, as when new programs in an IT landscape form links only to important hubs.

[1] The term was used by a revenue management expert throughout an interview to emphasize the booking class limitation to a discrete number of 26 alphabetical letters (refer to field data oS8).

I contend that a conceptualization of path dependence – or lock-in, its theoretical complement – must also take into account interaction patterns and growth processes. Beyond airline distribution, also organizational IT infrastructures illustrate the need to extend path dependence theory as they are characterized by "ramified webs of externalities and interdependencies" (Ciborra and Hanseth 2000:2) and are often highly independent from central control (cf. Hanseth 2002). When an organization is small, information can be managed using standard software. The information system architecture is simple and intelligible. When firms grow, data processing requirements increase. Constant changes that add new programs or extensions make IT infrastructures increasingly complex. Inertia builds up as new systems and links are constantly added. In large enterprises, standards diffuse and fundamental changes get out of reach. I view path dependence as a problem of standard diffusion in networks.

Consistent with this view, in what follows I develop a set of models that take interaction patterns and growth processes into account in explaining path building and path breaking. I apply these models to two empirical sites; the primary setting is global IT infrastructures in airline distribution where I examine the conditions under which a new path in passenger transportation may be created; in addition, I examine one model's implications for the evolution of an organizational IT infrastructure using a case from the recycling industry.

1.1 Motivation: The Example of Airline Distribution IT

To substantiate claims of path dependence, methodical advice suggests presenting empirical evidence on the influence of critical events, self-reinforcement, and lock-in (Sydow et al. 2012; Sydow et al. 2009). Consistent with Vergne and Durand (2010), I believe that such evidence will always remain partial as data collection on critical events is retrospective, self-reinforcing mechanisms in such complex settings – spanning across space and time – are accompanied by various negative feedback loops, and inefficiency claims are constructed by stakeholders on-the-fly. Nevertheless, I believe in the value of modeling. I draw on the booking class case, because I believe that it is relevant to illustrate the need to extend existing models of path dependence with respect to interaction patterns and growth processes. However, serious inertia in changing existing practices in the area of pricing – demonstrated by substantial evidence from a number of interviews and observations (refer to online supplements oS1 to oS21), as well as archival sources (refer to online supplements oS22 to oS39) – suggests that the booking class case is a well-chosen example of path dependence. This proposition is substantiated by the following statements from industry experts (refer also to Table S5 in the appendix):

> "*With the booking class topic you have hit a lock-in bull's eye. For a long time we try to get rid of these things.*" (Revenue management expert, refer to archival data oS35)
>
> *It will be difficult to depart from the booking class logic […] I do hope some scientist must be thinking that perhaps the time came to accept a booking with a passenger value but perhaps I am now voyaging into Mars.*" (Aviation expert, refer to interview oS21)

Consistent with Liebowitz and Margolis (2013), I believe that every relevant argument of path dependence should be complemented by a claim of inefficiency. With respect to the booking class standard, the claim goes as follows: the booking class standard enables effective collaboration among airlines, Global distribution systems (GDS), travel agents and other stakeholders in airline distribution. Total airline sales were estimated as 3,300 million bookings worldwide in 2012 of which 1,400 million came through the GDS (refer to Amadeus-internal report in oS24). The booking class standard supported a long period of successful growth in which additional marketing and pricing capabilities were built on top of existing booking class-based IT infrastructures (refer to expert statements in oS7 and oS16). An intense differentiation of organizational structures, routines, and IT systems is the precondition to performing advanced airline processes. Availability and pricing information can be exchanged between various organizational IT systems as well as across organizational boundaries. This compatibility enables significant synergies: the booking class standard is an important antecedent for additional revenues generated by interlining and codeshare tickets, which are offered through carriers' own channels directly as well as through the GDS's (refer to expert interview oS8 to oS10). However, growing evidence in the area of airline pricing and revenue management suggests that booking class-based practices are – at least theoretically – inferior from the perspective of individual airlines using them, as the booking class standard's implementation restricts adopters to a discrete instead of a continuous number of price points (Levin et al. 2009; also refer to expert interview oS2 and oS7 and archival material oS34). In particular, a carrier with a continuous number of price points could discriminate prices across different individual customers perfectly and would thus be able to generate incremental revenues which the carrier cannot do with the current systems in place today (Isler and D'Souza 2009; Pölt 2011). To establish a new standard in airline distribution, airline industry association IATA has started an initiative, the New Distribution Capability (NDC) initiative (refer to IATA 2013 for more information). Yet, it hasn't really gotten off the ground. IATA faces difficulties in establishing the new standard.

Viewed together, I believe that the booking class standard is a local instead of a global optimum (refer to the "hills" in Figure 1). Whether airlines will be able to overcome switching costs and coordination problems is subject to much debate (Westermann 2013).

Figure 1 structures problem areas in airline distribution IT related to the persistence of the booking class. In the figure, I distinguish between industry-level dynamics, on the left, and organizational-level dynamics, on the right. On the industry level, I identified three main problem areas: (1.) airline coordination problems, (2.) the market structure, and (3.) the role of aggregators. It is useful to distinguish airline coordination problems from decision-making by other stakeholders due to the complexity of the industry. I exclude GDS and aggregators from explicit consideration as detailed, historical studies on GDS platform competition exist already (Copeland and McKenney 1988; Farhoomand 2000; Granados et al. 2008; Schulz et al. 1996) and the scope had to be limited. This focus is indicated by the dashed squares in the figure. As shown on the right of Figure 1, it is argued that organizational level processes further reinforced the booking class standard.

Essentially, the booking class path was driven by "powerful network effects" on a market level (refer to Figure S2 in the appendix). After airlines had established early computer reservation systems, retail automation in the US in the late 1970's led to an increasing adoption of GDS by travel agencies (Copeland and McKenney 1988). Increased use of GDS by travel agents in turn incentivized airlines to exploit increasing returns from content publishing via the GDS. Moreover, demand-sided scale economies created a rationale for airlines to focus their efforts on a limited number of GDS and, in the following years, a consolidation to a few dominant platforms took place (Copeland and McKenney 1988): SABRE became dominant in the US (Copeland and McKenney 1988) and Amadeus in Europe (Schulz et al. 1996). All major airlines subscribed to the GDS and adopted compatible sales systems incorporating GDS standards such as booking classes. The GDS importance continued despite significant effort to transform airline distribution to e-commerce and the internet age (Farhoomand 2000; Granados et al. 2008).

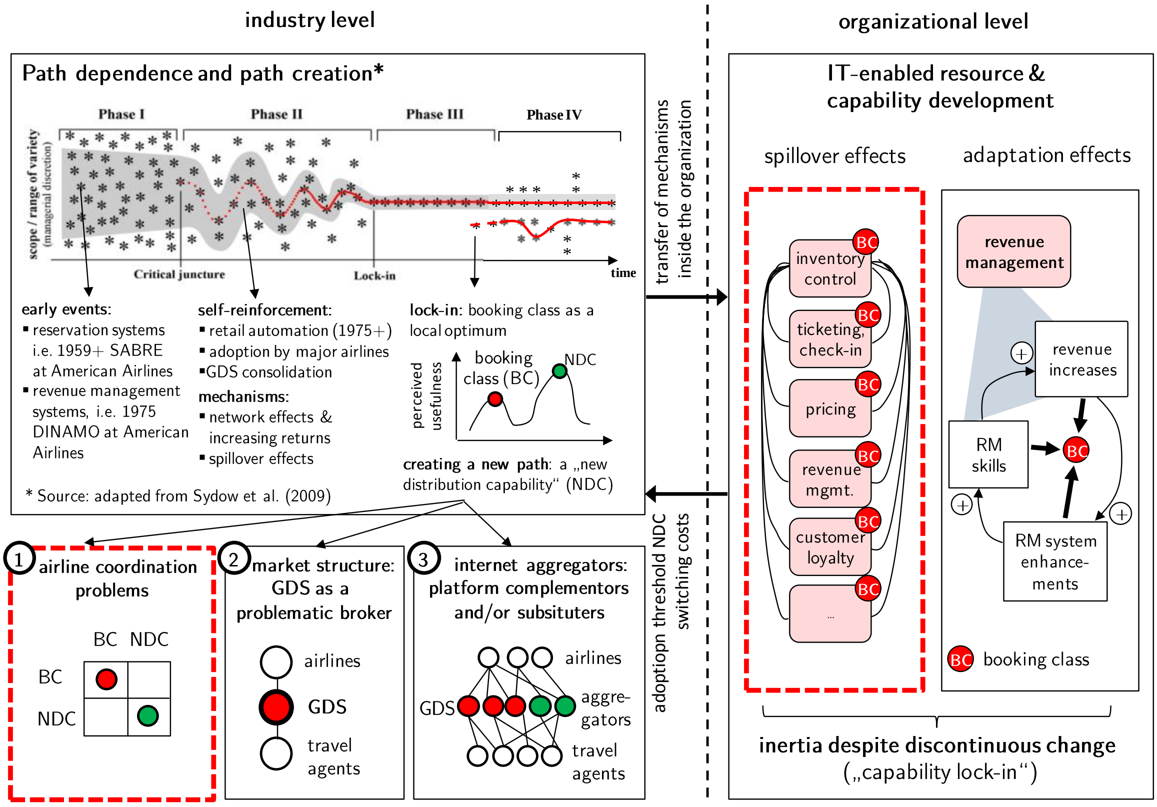

Figure 1. Booking class-related problem areas in airline pricing and distribution

Booking classes raise problems today going beyond the technical dimension because the standard became the underlying core pattern for airlines' capabilities in such important areas as pricing. Essentially, pricing refers to "a firm's ability to set the right prices" to capture potential rents from market-based transactions (Dutta et al. 2003:616). Consistent with Dutta et al. (2003), I view pricing as an organizational capability. Airline pricing has its most important antecedents in a set of methods and tools referred to as "revenue management" (Cleophas and Frank 2011; Talluri and van Ryzin 2005). It goes as far back as Smith et al.'s (1992) case study of successful yield management implementation at American Airlines, and Littlewood's (1975, 2005) approach to pricing forecasting and optimization. Since then airlines developed several generations of increasingly advanced revenue management (RM) approaches, from overbooking to origin-destination bid price revenue management (Lehrer 1997; Lehrer 2000). Booking classes became a central parameter in deciding whether to accept or reject a booking request (Talluri and van Ryzin 2005:176). Refer to Figure S3 in the appendix, which shows that each generation of revenue management technology has used booking classes more intensively.

Today, the booking class is ubiquitous in almost any marketing/distribution-related airline process (refer to interviews oS1 to oS9). Figure 2 depicts important activities in which the booking class standard spilled over. Ticketing, check-in and pricing systems refer exclusively to booking classes (refer to interview oS9). Beyond that, it became central for codesharing, customer loyalty and other processes such as revenue integrity and reporting. Table S6 in the appendix substantiates the booking class usage in each of these activities.

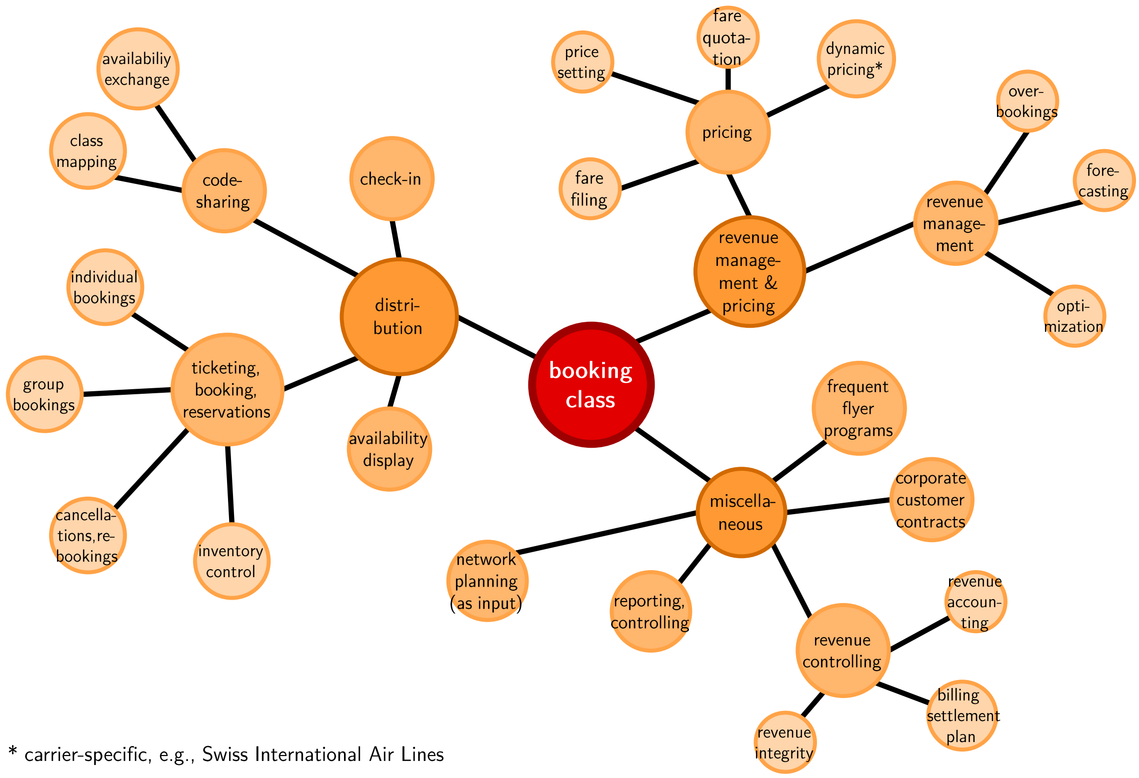

Figure 2. Diffusion of booking classes in airline activities. Source: own investigation

Bartke (2013:20) notes that "the pervasive use of the booking class standard throughout the distribution, booking and check-in processes has so far prevented the adoption of [...] newer methods in practice". To imagine the magnitude of switching costs consider first the example of British Airways. British Airways replaced its legacy inventory in 2002 (refer to report by Amadeus in oS40): vendor Amadeus' effort was approximated as 180 person years, 13,400 British Airways employees were trained, 48,190 terminals had to be connected, and 51 core IT systems were interfaced, 2.5 million passenger name records were migrated; more than 300 British Airways employees were drawn in the project over two years. Moreover, while the inventory is one key IT resource in airlines' distribution strategy, dozens of other important systems have to be considered: the revenue management system, the customer loyalty system, the reporting system, to name a just few, in more than 1,000 commercial airlines worldwide.

Due to the standard-setting role of the airline industry, airline distribution standards also spilled over to other industries such as hotels, railway companies, or car rentals (refer to

Cleophas et al. 2011 for an overview of applications of revenue management and pricing practices across different industries). These interdependencies today strengthen the impact of booking class-related inertia.

Furthermore, when a top management team – as in individual airlines – can exhibit control, switching standards may be feasible, but as booking class-related activities are interorganizational and embedded in global distribution infrastructures further constraints diminish airlines' scope of action. Two examples are codesharing and corporate customer contracts. Codesharing involves two carriers: The marketing carrier, selling a flight, and an operating carrier, operating the flight. On the strategic level, codeshares are negotiated between those two carriers which not only gives rise to controversies regarding revenue sharing (Gerlach et al. 2013; Gerlach 2013; Hu et al. 2013) but also with respect to finding an appropriate mapping of customer categories to exchange flight availabilities and to transfer bonus miles. Booking classes are a well-established yet unquestioned instrument. Corporate customer contracts, to give another example, add a cognitive dimension to the book class inertia. Not only do corporate customers stick to booking classes "like drowning people" (refer to RM expert in oS10) as they guarantee them privileges, status and prestige, sales departments also speak to customers in the language of booking classes, negotiating bonuses based on them and inscribe them into contracts. These examples confer the booking class a cognitive and material dimension spanning organizational boundaries. Displacing all booking class-based systems in the short or medium term seems unrealistic (refer to RM expert statements in oS11 to oS14).

In the first part of this thesis, I suggest a model that portrays how inertia builds up by new elements being added to an existing system, which makes switching increasingly implausible. In the second part of this thesis, I suggest a model that contributes to the NDC debate by examining scenarios regarding the creation of a new path in airline distribution.

1.2 Research Approach

This thesis draws on a number of data collection and analysis methods:

- Expert interviews
- Case study research
- Modeling of empirical data (i.e. network analysis) and
- Agent-based simulation experiments

Throughout my research, I followed Gilbert and Troitzsch's (2010) guidelines on how to conduct agent-based simulation research. Agent-based models are useful for theory building as they can facilitate understanding about complex, nonlinear phenomena in (inter-) organizational contexts (Davis et al. 2007; Gilbert and Troitzsch 2010; Squazzoni 2012). Positioning my work in information systems research, I consider agent-based modeling useful for research on path dependence and standard diffusion as it can illuminate multi-level phenomena incorporating a large number of heterogeneous, interacting agents (cf. Kiesling et al. 2011; Weitzel et al. 2006). While I appreciate the role of simulation modeling for decision support (Law 2007), this research is not predictive in nature but intends to inform research and managerial thinking on nonlinear, path-dependent processes in complex IT infrastructural arrangements.

After reviewing the literature on path dependencies in IT infrastructures, I began my empirical research by entering the field site of a German recycling company. I used a case method (Yin 2013) to study the IT landscape of Recycle Inc.[2], a privately-held company with 9,000 employees. The company was selected as a representative example for a medium to large-sized enterprise with a segmented (multi-corporate) structure. Founded in 1968, the company grew from waste management to several other domains, acquired and split off subsidiaries regularly, and thus captured well how path dependencies in organizational IT infrastructures unfold. To limit the scope of the investigation, one business domain was selected as initial interviews confirmed that the company faced problems to consolidate its fragmented, legacy-centric domain IT landscape. Based on an in-depth study of one core enterprise resource planning (ERP) system – including 13 expert interviews (refer to oS41 to oS53) – I recognized that standards, inscribed early in the platform, often diffuse in an organization by new programs and extensions being added. When an IT infrastructure grows, this will materialize in complex interdependencies between various IT systems. While extensions of existing systems aim to work around limitations, they in fact reinforce established standards by creating barriers to change the overall system. While my initial presumption was that particular information systems follow a path-dependent trajectory, I gained the impression that standards are an even more severe motor of path dependence as they become inscribed in *various* systems and persist despite the replacement or adaptation of single systems.

I focused effort to finding an extreme case of path-dependent standards. I turned to the airline industry and the booking class example. My perception of the importance of standards became amplified in several interviews with experts in airline distribution IT and revenue management (refer to interview oS1 to oS6; oS15 to oS21) on problems in introducing dynamic pricing methods. I sensed that problems in replacing booking class-based practices are not limited to local settings but increasingly interorganizational. Therefore, my analysis shifted – based on the problem instance – from individual organizations' IT infrastructures to problems of coordination within an industry. To specify a model, I focused on an intensive collaboration with Swiss International Air Lines (SWISS), a prestigious European full service carrier. Interviews confirmed that SWISS faces problems displacing booking class-based practices by dynamic pricing methods and that the carrier had started several initiatives that had not yet been successful (refer to interview oS7 to oS14).

Based on the problem, I investigated models of path dependence and standard adoption. I was disappointed by existing path dependence models' qualities with respect to explaining (*a*) how inertia actually builds up over time and (*b*) how paths can be broken in settings with complex interactions among large numbers of distributed actors. For instance, Arthur's model of path dependence and increasing returns – a seminal example – assumes that each new agent entering a network forms links to all other agents. This form of interaction is very particular and mischaracterizes most real world situations. I found that Arthur's model results in a too stark "winner-take-all" characterization of diffusion outcomes (Fichman 2004); hence, it was only of limited value for my investigation.

[2] To protect privacy, I agreed with the company's IT management to not enclose company names

Therefore, I explored another class of models on standardization problems from an economic tradition in information system research (Domschke and Wagner 2005; Weitzel et al. 2006; Weitzel et al. 2000). These models had already incorporated important aspects of the network structure to explain how standards diffuse among actors selecting standards. These models shed light on standardization gaps (Weitzel et al. 2006), penguin effects, excess inertia (Liebowitz and Margolis 1996; Weitzel et al. 2006), and gateway technologies (Buxmann et al. 2011; David and Bunn 1988; Farrell and Saloner 1992). However, these models have limitations with respect to real world problems of path dependence in complex IT infrastructural arrangements. Firstly, many of these models use a central optimization approach. Hence, a central planner is assumed that can oversee and optimize the entire network with respect to the standards used (Domschke and Wagner 2005). This approach is restricted to particular problem instances within firms or in very centralized networks. Only few models propose decentralized approaches to agent decision-making (e.g. Weitzel et al. 2006). They are, however, held back by the assumption of simultaneous decision-making of all agents. This view is limited, as it requires complete information on all other agents' standardization costs, number of interaction partners and benefits from mutual standardization.

Consequently, I suggest a new set of models to analyze IT infrastructure path dependence. Drawing on network analysis as my theoretical foundation (Jackson and Zenou 2013; Jackson 2008b), a first model (the "growth model") highlights growth processes in networks showing how inertia builds up and how standards increasingly diffuse within a growing system. The model sets itself apart from other models by incorporating new ways how to initialize the network and by a unique network growth strategy: agents entering the network form links to a particular number of other agents uniformly at random and to another fraction of agents as friends-of-friends (Jackson and Rogers 2007). I show that the model is able to reproduce findings from seminal models of path dependence and I apply the model to examine how random, preferential, or hybrid growth affects path building.

Building on network diffusion models (Elliott et al. 2014; Jackson 2008b), I then suggest a second model (the "contagion model") that taps into the extent to which new standards diffuse by triggering selected nodes in a network and tracking the subsequent domino effect running through the network. The model reproduces stylized facts from seminal models of innovation diffusion. Furthermore, I demonstrate the model's value to assess scenarios with respect to the diffusion of a new standard in airline distribution IT.

1.3 Thesis Outline

Figure 3 outlines this thesis. Part I introduces problems of IT infrastructure path dependence: chapter 2 reveals the link between path dependence theory and important streams of information systems research; it also introduces selected formal models of path dependence and suggests a network perspective as my theoretical foundation. Chapter 3 shows the need for research and outlines the research questions.

Drawing on a distinction between path building and path breaking (Sydow et al. 2009), the next two parts present the models and main results. In particular, part II concerns questions of path building and part III investigates path breaking.

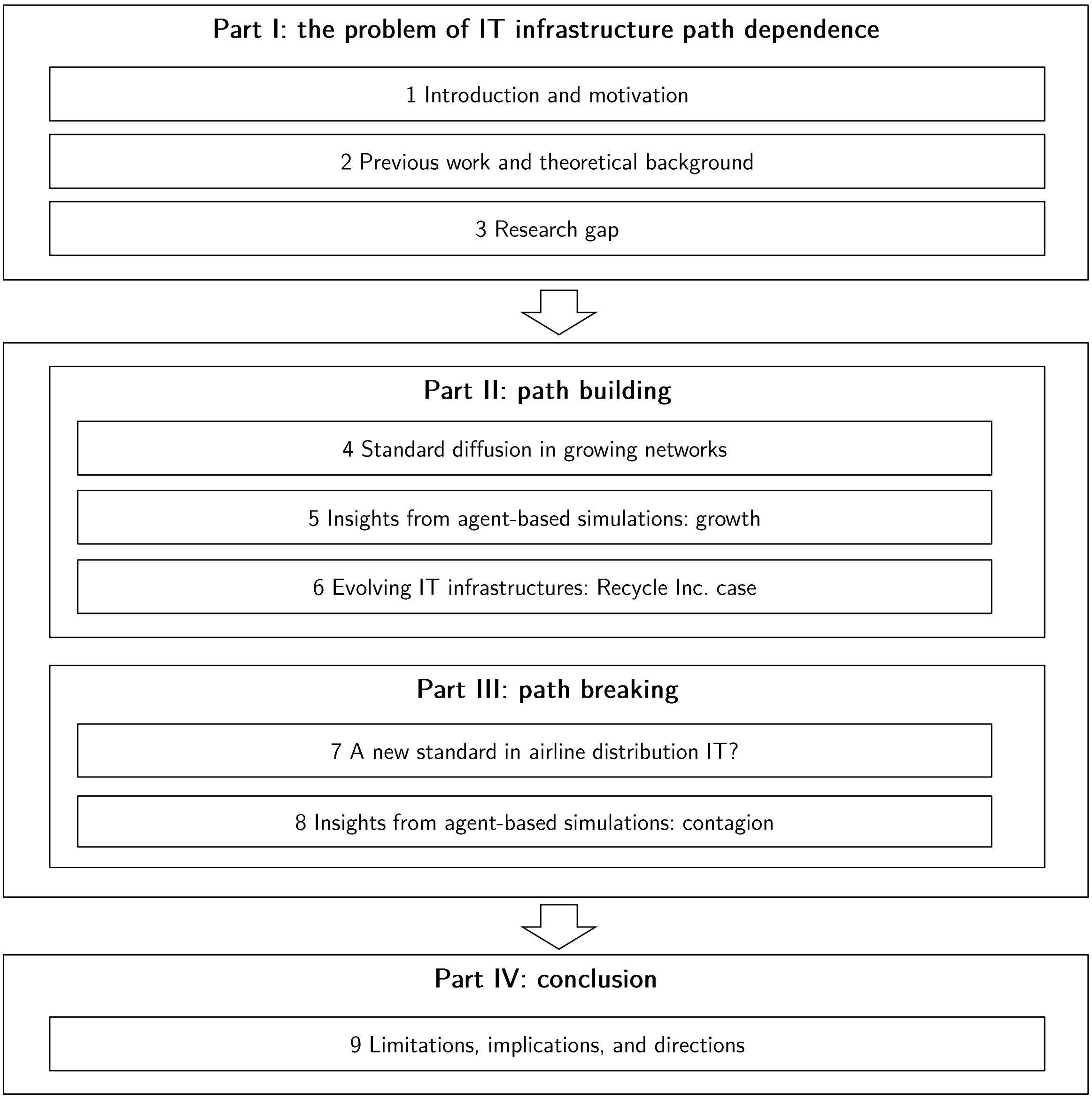

Figure 3. *Outline of this thesis*

Part II investigates how a network's growth logic affects path building. In particular, chapter 4 suggests a new model of path building to structure network effects that pays more attention to the mechanics of link formation in making sense of clustering dynamics such as "islands of shared technology" that characterize many real world settings. Chapter 5 then presents results from experiments on growing networks to test propositions on the effect of different growth logics on path building. As a final section of Part II, chapter 6 introduces the case of Recycle Inc. to demonstrate the value of the model in understanding the evolution of organizational IT landscapes. Furthermore, I suggest a method that supports IT managers and architects in assessing system embeddedness and continuance inertia. I build on established measures of centrality from network analysis to assess the criticality of IT systems with respect to their architectural embeddedness.

Part III intends to add our understanding on path breaking. In particular, Part III focuses on when and where a new standard diffuses to a nontrivial fraction of agents in a network. Drawing on the example of path creation in airline distribution IT, chapter 7 introduces empirical requirements, describes empirical data, and presents results from a structural analysis of an empirical network of codeshares in global distribution IT. Following suit, the remainder of chapter 7 introduces a contagion model that can be applied to examine standard diffusion in this network. Chapter 8 presents insights from agent-based simulations including several important extensions to the base model.

Part IV (chapter 9) summarizes the research, discusses limitations, concludes, and introduces an agenda for future research.

Chapter 2

Previous Work and Theoretical Background

I start my examination of previous work by exposing the link between path dependence and three recent and fruitful streams in information systems research: IS strategy and organization (chapter 2.1), research on information infrastructures and standards (chapter 2.2), and research on diffusion and adoption (chapter 2.3). Thereafter, a network perspective is introduced as the theoretical foundation of this thesis (chapter 2.4). Furthermore, I introduce selected formal models of standard diffusion and path dependence (chapter 2.5). Firstly, I turn to simple yet powerful urn models that are foundational for the path dependence model by Brian Arthur (1989). Secondly, I discuss models on the diffusion of standards and innovations. The chapter ends with a comparison of various models (chapter 2.6).

2.1 Path Dependence in IT Strategy and Organization Research

2.1.1 Concurrent Perspectives on Inertia in IT Infrastructural Arrangements

To begin, inertia generally denotes the “power of resisting by which every body, as much as in it lies, endeavors to preserve its present state” (Newton 1846:72). Inflexibilities, change barriers, persistence, rigidities, resistance, lock-ins and path dependence are common themes in information systems research on IS strategy, structure, and organizational impacts being discussed from various perspectives such as the business value of IT, IT flexibility, IT alignment, and IT architecture.

I start by turning to research on IT business value. Traditionally, much of the research in this tradition has been concerned with the controversial question of how business value is created from investments in IT (cf. Brynjolfsson 1993; Soh and Markus 1995; Zhu 2004; Aral and Weill 2007; Kohli and Grover 2008; Mithas et al. 2011; Mithas et al. 2012). The predominant paradigm is the resource-based view (RBV) of IT (Kohli and Grover 2008; Melville et al. 2004; Piccoli and Ives 2005) that goes as far back as Bharadwaj's (2000) notion of IT as a capability, consisting of a complex bundle of technical, human, and intangible skills that potentially enable a firm to create business value.

An interesting implication of work in this tradition for path dependence research – generally more interested in positive consequences of IT usage – is that after decades of controversy, much attention has been devoted to complementarities as a source of IT business value creation (Kohli and Grover 2008). In its canonical form, complementarities between two elements A and B have be assumed if the marginal benefit of investments in A increase with the level of B, and vice versa[3] (Porter and Siggelkow 2008:44). The emerging

[3] Further side conditions have to hold to assume that the relationship is robust that captures the effect of a joint appearance of (investments in) two activities A and B on some performance measure P. In contrast to substitution relations, complementarities imply that P increases with increases in A or B (Porter and Siggelkow 2008:44).

key insight was that IT investments can only create value in combination with other, synergetic factors. Based on that insight, many studies in the 'business value of IT' tradition have demonstrated the importance of complementarities between different elements of an IT infrastructure to explain IT business value (e.g. Tanriverdi 2005; Zhu and Kraemer 2005; Tanriverdi 2006; Aral and Weill 2007; Bharadwaj et al. 2007; Lee 2008; Nevo and Wade 2010). Complementarities – in form of super-additive performance or sub-additive cost effects – can result, for instance, from shared IT infrastructures and IT management processes among subunits. Examples for such processes include strategic IT planning, IT human resource management, and IT vendor management (Tanriverdi 2006). Other research on IT business value has demonstrated the positive interaction effect from aligned technical investments in the development of the IT platform, and complementary competencies as well as IT practices that may unleash a positive feedback spiral resulting in higher firm performance (Aral and Weill 2007). In addition, work by Aral et al. (2006) has shown a positive performance effect that can result from subsequent investments in different, complementary IT components; companies learn from prior IT investments in one application area and are thus able to facilitate this knowledge in a later stage. Their research illustrates that companies that implement an ERP system successfully can subsequently gain in performance when implementing a customer relationship management (CRM) system.

Cases of inertia have long been recognized in the RBV literature, but are mostly discussed as a side-note or anomaly in the respective papers. Bharadwaj (2000:187) for instance – in her celebrated essay on IT as a capability – notes that some firms fall into "rigidity traps" facing enormous barriers to change with their existing infrastructures. Referring to a study on financial service companies, she observes that cost pressures and resistance by IT staff often prevents necessary change with respect to existing legacy IT infrastructures. Little research in the tradition of the RBV has, however, followed up on her trail.

This is surprising given the fact that extended research from organization theory and path dependence has long noted that self-reinforcement – arising for instance from complementarities – can lead to undesirable path dependencies and capability lock-ins (Sydow et al. 2009). From organization theory we are well aware of "competency traps" (Siggelkow and Levinthal 2005) and various investigations have shown that the positive impact of capabilities may flip over from core competencies to core rigidities after a period of successful growth (Leonard-Barton 1992; Sydow et al. 2009). Examples in this theme appear multiple times in studies from organizational theorists, e.g. for firm strategizing processes (Burgelman 2002), knowledge acquisition processes (Cohen and Levinthal 1990), product development processes (Leonard-Barton 1992) and organizational learning processes in general (March 1991). In this tradition, positive feedback captures the core idea of how capabilities lock in (Sydow et al. 2009). Positive feedback in a set of complementary elements constantly reinforces a set of practices, processes, or capabilities. Mutual adaptations over time make it more and more attractive to choose the given set of practices, which unintentionally locks in the "deep structure" of capabilities (Sydow et al. 2009:599). Eventually, "individual actors are no longer able to strategically influence population-level outcomes or are trapped in local-level action patterns" (Dobusch and Schüßler 2013:20). This is how path dependence constructs capability lock-ins.

The idea of *dynamic capabilities* has then extended and informed existing RBV research to explain how to reconfigure existing capabilities to maintain flexibility in rapidly changing environments (Eisenhardt and Martin 2000; Teece et al. 1997). Dynamic capabilities are defined as a "a company's ability to integrate, build, and reconfigure internal and external capabilities to address rapidly changing environments" (Teece et al. 1997). They are distinct organizational processes allowing an organization to (*i*) sense emerging trends and changes in the environment early, (*ii*) seize opportunities to follow these trends, and (*iii*) transform organizational capabilities and resources accordingly (Teece et al. 1997). According to this view, organizations need the ability to *add*, *shed*, and *integrate* resources and capabilities in a flexible manner in order to transform operational capabilities (Eisenhardt and Martin 2000). Various studies in the tradition of the RBV have tried to operationalize dynamic capabilities in the context of IT infrastructures (Bhatt and Grover 2005; Piccoli and Ives 2005; Sambamurthy et al. 2003). An extensive research tradition on strategic information systems planning (SISP), for instance, explicitly or implicitly assumes that SISP is a dynamic capability that helps organizations achieve competitive advantages (cf. Galliers 1991; Segars and Grover 1998; Kearns and Lederer 2003; Newkirk and Lederer 2006). However, a thorough testing of whether and to what extent SISP is a dynamic capability is impeded by operationalization problems (Fuerstenau et al. 2014).

Other concepts have been suggested to extend the RBV with respect to explaining how operational capabilities can be reconfigured in value-creating ways. For instance, the concept of *improvisational capabilities* has been introduced – the possibility of predicting competitive advantages in turbulent environments (Pavlou and El Sawy 2010). Improvisational capabilities denote an organizations ability to "spontaneously reconfigure existing resources to build new operational capabilities to address urgent, unpredictable, and novel environmental situations" (Pavlou and El Sawy 2010:443). A distinction of planned versus unplanned change is introduced to theorize successful changes (Orlikowski and Hofman 1997; Pavlou and El Sawy 2010).

On a similar note, research on IT flexibility, as another important stream of IS strategy and organization, has also – more implicitly – been concerned with inertia, as the goal of becoming more flexible or agile is framed as a question of overcoming existing inertia (Byrd and Turner 2000). Consequently, to become or remain competitive, firms should strive for IT flexibility (cf. Byrd and Turner 2000) or business agility (cf. Weill et al. 2002; Sambamurthy et al. 2003; Setia et al. 2007). IT flexibility[4] denotes a firm's ability to enable business process innovations which will in turn create business value for organizations (cf. Byrd and Turner 2000:168; Kohli and Grover 2008:26). IT flexibility allows organizations to respond to environmental changes swiftly (cf. Byrd and Turner 2000:170) and, most desireably, enables organizations to sense changes in their environment early, react

[4] Byrd and Turner (2000:168) define IT infrastructure flexibility as „the ability to easily and readily diffuse or support a wide variety of hardware, software, communications technologies, data, core applications, skills and competencies, commitments, and values within the technical physical base and the human component of the existing IT infrastructure". Business agility has been defined as an organizations' ability to innovate and to introduce new products swiftly (cf. Tiwana and Konsynski 2010). An IT infrastructure thereby denotes "a collection of reliable, centrally coordinated services budgeted by senior managers and compromising both technical and human capability" (Weill et al. 2002:59).

proactively and shape their environment through their superior IT infrastructure capabilities (cf. Andresen and Gronau 2005). Sambamurthy et al. (2003), for instance, treat IT as a real-option that is valuable because “it provides an opportunity to realize benefits if or when the need arises” (Kohli and Grover 2008:26). Hence, IT flexibility becomes a source of sustainable competitive advantage (cf. Kohli and Grover 2008). Overcoming inertia is put on the managerial agenda: by selecting the right initiatives that maximize business value, organizations should (or will) increase strategic agility (cf. Weill et al. 2002).

Viewed together, one key assumption underlying many of these predecessors is the control idea[5] (Ciborra 2000:21f.). According to Ciborra (2000), the control idea refers to assuming that targeted interventions will be able to align organizational IT infrastructures in accordance with managerial plans and directions. This is illustrated most forcibly by existing research treating IT as a portfolio (Ciborra 2000:33-38). Thereby, it is assumed that IT presents a bundle of investment options that can be re-allocated flexibly by managers selecting the right initiatives to maximize the business value of IT (cf. Ward and Peppard 2009). Factors impeding flexibility are misfits in contextual conditions within the organization: for instance a lack of IT governance – how organizations structure their IT decision rights (cf. Weill and Ross 2010) – or lacking senior management commitment to enterprise architecture (cf. Ross et al. 2006).

While the RBV and its many important extensions have mostly concentrated on how to “get a grip on” inertia from a managerial point of view, an extensive body of research, mostly drawing on vivid, in-depth case studies has illuminated many important antecedents, drivers, and consequences of inertia in complex organizational IT infrastructures. How and why will inertia arise in the first place? One of the main themes in this literature is the consequences that arise from the entanglement of technical systems and human agency (Boudreau and Robey 2005; Leonardi and Barley 2008; Robey and Boudreau 1999). Many studies in this tradition suggest that inertia arises as *human actors* – users, managers, or other stakeholders – often resist, hinder, block, veto or implicitly withdraw new systems and technologies for various reasons such as that they worry about changes in their routinized, and often highly institutionalized work practices (Orlikowski 1992), they worry about losses in power, influence or status (Markus 1983), or they perceive constraints from existing management systems such as budgeting and incentive-setting (Leonard-Barton 1992). Underlying explanations arise from culture (cf. Cooper 1994), politics (cf. Markus 1983), institutionalization (cf. Orlikowski 1992; Orlikowski and Barley 2001; Orlikowski 2007) or organizational learning (cf. Robey and Boudreau 1999). Many pertinent cases can be found in the literature. Orlikowski (2000), for instance, observes limited groupware use by users reinforcing and preserving the status quo. Similarly, Boudreau and Robey (2005) find users initially avoiding a new ERP system as much as possible as it doesn’t fit with their learned practices and way of doing things.

Another common theme is the nature of the IT artifact itself (Leonardi and Barley 2008; Orlikowski and Iacono 2001). Essentially, the underlying observation in many of these articles is that early decisions, intentions, perceptions, and cognitive representations from

[5] In the words of Byrd and Turner (2000:170), “high flexibility corresponds with a high control of the organization with respect to the environment”.

designers, managers, key users, or other stakeholders become implicitly or explicitly *inscribed* in early stages of the technology lifecycle which often creates unchallenged, taken-for-granted realities for organizational users drawing on these systems in later stages (Orlikowski and Robey 1991; Orlikowski 2000). Markus et al. (2000), for instance, note that many of the problems firms experience in later phases of an ERP life cycle originate earlier, but remain unnoticed or uncorrected. Volkoff et al. (2007) portray how ordering routines become inscribed in a complex ERP system, which gives them a material aspect that inhibits their change in a later stage. Leonardi (2011) draws on an in-depth study of engineers' use of simulation tools to show that changes in the technology-in-use often make particular complementary changes of work routines more beneficial, and vice versa. From this he suggests a path-dependent trajectory where systems and routines are constantly adapted and (recursively) imbricated based on the capacities that each of these subsystems offers. From a thorough reading of this literature, we can thus learn that early decisions on a deep, architectural level are often inscribed into systems and tools that will be in organizational use over extended time periods. These design patterns on a deep, architectural level can be perpetuated or even reinforced by user-driven processes of constant adaptation, improvisation, and bricolage (Masak 2006b:268).

Finally, inertia should also be viewed from an IS architectural perspective (Ross et al. 2006). Information systems become embedded in work practices and integrated with other systems on a technical level, and the larger the embeddedness, the less desirable replacement decisions become (Furneaux and Wade 2011). Furneaux and Wade (2011) observe that a system's embeddedness in an organization is a source of inertia. According to this view, the "extend to which the use of information systems is part of organizational activity (…) impose significant constraints on discontinuance intentions" (ibid:579). One implication is that, as suggested by the IS architectural viewpoint, embeddedness is determined by a system's position in the IS architecture. More precisely, the extent of embeddedness will be formed along several dimensions. Furneaux and Wade (2011) point to a system's embeddedness in work practices and the technical dependency of a system on other systems. Regarding technical integration, a survey among IT managers found that systems integrated more strongly, became replaced less frequently (ibid:590).

In their celebrated book on enterprise architecture as a strategy, Ross et al. (2006) draw on the case of an investment bank whose legacy systems were so cobbled together that "it was a miracle they worked" (ibid:11). The complex architecture created rigidities and excessive costs as systems had to be adapted manually to respond to each new business initiative. Schneberger and McLean (2003) argue that the computing complexity of an IT architecture – the extent to which software becomes difficult to maintain or manage – increases exponentially as a function of a system's degree of distribution: while the complexity of (single) components decreases almost linearly with a systems degree of distribution, the system complexity with respect to the number, variety, and change rate of interfaces increases exponentially. Thus, the complexity of the overall architecture increases also exponentially.

2.1.2 Standards as the Underlying Core Pattern for Organizational Capabilities

When capabilities become inert, an underlying *core pattern* – may it be a decision or action pattern – cannot be changed despite change requirements from the environment of the organization (Sydow et al. 2009). I argue that this core pattern may be a technical standard. While this appears at odds with capabilities defined as *distinct* resource allocation patterns embedded in the organization (Dosi et al. 2000), I believe this is in no way a contradiction as companies have to force selections concentrating on particular areas of application to cope with a potentially infinite number of internal and external problems (cf. Schreyögg and Sydow 2010). Consequently, standards on a technical level may remain unquestioned as long as they allow developing capabilities enabling the company to achieve a competitive advantage. This may even apply to dynamic capabilities. According to Eisenhardt and Martin (2000:1108), "while dynamic capabilities are certainly idiosyncratic in their details, the equally striking observation is that specific dynamic capabilities also exhibit common features that are associated with effective processes across firms". This appears particularly reasonable considering the *IT-enabled* nature of many of today's capabilities building on complex IT systems, practices, and skills (Aral and Weill 2007; Kohli and Grover 2008; Nevo and Wade 2010, 2011).

Possessing a capability implies excellence of a firm in a selected area of application (Schreyögg and Kliesch-Eberl 2007). This excellence may be attributed to the firm because of constant above-average performance or pure myth (Meyer and Rowan 1977; Schreyögg and Kliesch-Eberl 2007). Improving a capability, however, requires effortful learning and enhancement processes in every case (Eisenhardt and Martin 2000). Building a consistent and reliable IT infrastructure to enable such capabilities has also been shown to be a protracted learning and adaptation process over extended time periods (Ross et al. 2006). We know from research on IT-enabled capabilities that IT assets and organizational resources form possibly synergetic systems that enable a firm to realize IT business value (Nevo and Wade 2010, 2011). According to this view, a synergy is, however, by no means preprogrammed. "In fact, emergent capabilities can be negative, neutral, or positive" (Nevo and Wade 2010:168). Taking a dynamic perspective on capability developments, we know from research on path dependence that *positive feedback* in organizational contexts first promote gains with respect to a specific output variable and may later flip over to a negative value contribution (Beyer 2005; Page 2006; Sydow et al. 2009). Alongside Dobusch (2010), Dobusch and Sydow (2011), and Dobusch and Schüßler (2013), I assume that complementarities in IT infrastructures can unleash self-reinforcement that may flip over to lock-in.

2.1.3 Discussion and Conclusion

From this brief review of the literature, I can draw several conclusions. Firstly, it is useful to distinguish different levels of an IT infrastructure at which inertia can arise. Most importantly, I believe it is useful to discern the level of single systems in single sites and the level of infrastructures. Tracing the trajectories of individual systems is illuminating and we have learnt from many in-depth studies that sources of inertia can arise from various factors related to the embeddedness of particular IT systems in organizations, as well as from processes of inscription, institutionalization, and routine building. A single systems view, however, grossly mischaracterizes the distributed nature of today's IT systems

(Henningsson and Hanseth 2011; Monteiro et al. 2013; Williams and Pollock 2012). According to Hanseth (2002), “the evolution of the kinds of IT infrastructures we are using today – integrating numbers of systems across organizational and geographical borders - significantly differs from the traditional view on information systems”. I therefore see a greater need for research on inertia in ensembles of information systems.

Secondly, we have learnt from the RBV that complementarities among technical and non-technical elements of an organizational IT infrastructure are key to understanding IT business value creation (Kohli and Grover 2008). Synergies arise when organizations build a reliable IT infrastructure, complemented by IT skills and practices, and successfully combine this infrastructure with existing organizational resources to form emergent capabilities (Nevo and Wade 2010, 2011). Complementarities potentially unleash a self-reinforcing dynamic that enables firms to achieve a competitive advantage (Aral and Weill 2007). Based on organization theory, I, however, presume that self-reinforcement is a two-sided sword: as any other organizational capability, massively IT-enabled capabilities can also flip their value-contribution from core capabilities to core rigidities (Leonard-Barton 1992; Sydow et al. 2009). The question that arises is whether and to what extent organizations are able to adapt their existing capabilities to react swiftly to environmental changes. Several concepts have been proposed to theorize when and how organizations can reconfigure their existing (IT-enabled) capabilities. My brief review focused on the notions of IT flexibility (Byrd and Turner 2000), dynamic capabilities (Teece et al. 1997), and improvisational capabilities (Pavlou and El Sawy 2010).

Turning to work by Heinz von Foerster (2010), I further group existing approaches by the extent to which they assume that IT infrastructures are trivial or nontrivial machines. Trivial machines transform inputs to outputs and the transformation function can be understood, modeled, and potentially altered by an outside observer. Nontrivial machines are, in contrast, defined by nonlinear, recursive, complex relationships that remain opaque or partial to an outside observer. I believe that many works on enterprise architecture, IT flexibility, and the business value of IT treat IT infrastructures as trivial machines. I share Ciborra's (2000) skepticism with respect to the validity of the underlying core assumption of existing concepts such as IT flexibility: existing research has favored the control idea, presuming that management is able to intentionally control the directions of IT infrastructure development processes by selecting initiatives that maximize the value of an IT portfolio on-the-fly (Ciborra 2000:21f.). This however, often conflicts with unintended, path-dependent consequences of small yet decisive decisions that could not be foreseen at the time when these decisions had to be made (Ciborra 2000:33).

Viewed together, Figure 4 shows how I position my research in relation to predecessors in the field of IS strategy and organization. On the vertical axis, I show the level of analysis which spans from single systems in single sites (at the bottom) to a higher level of analysis of IT portfolios, architectures, or infrastructures. On the horizontal axis, I depict the stand that is taken by the respective approaches towards complexity as described by von Foerster.

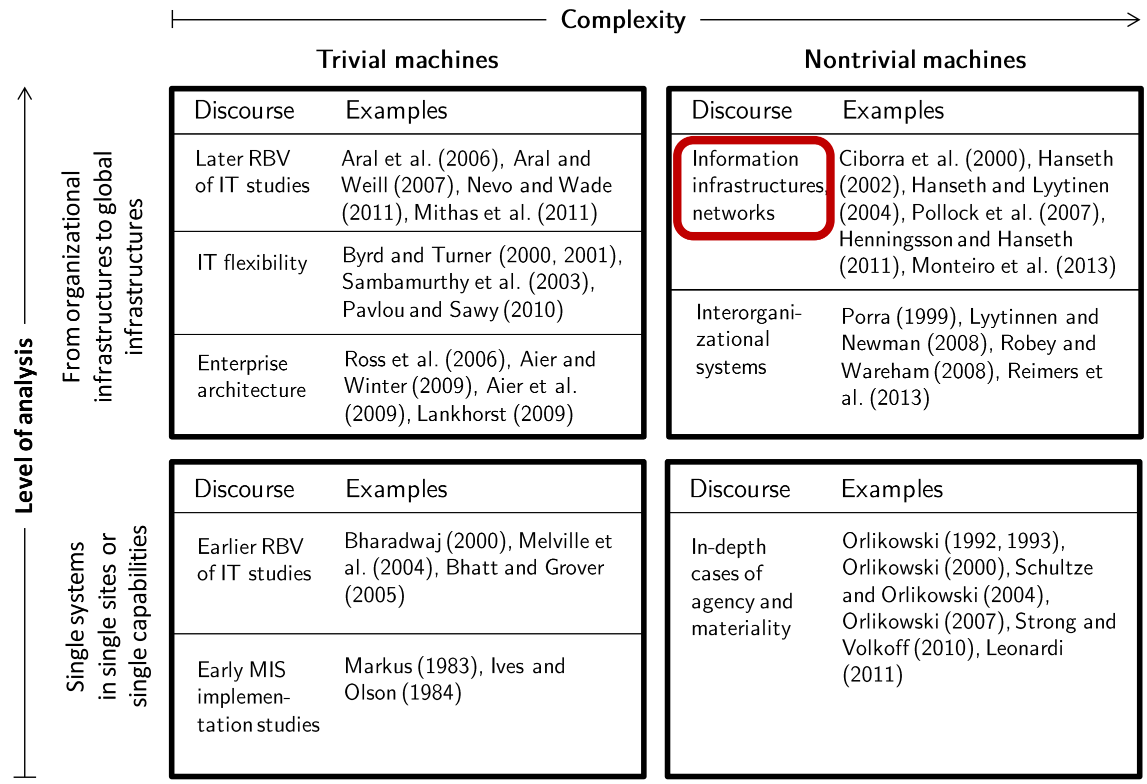

Figure 4. Positioning in literature on IS strategy and organization

I position my work in the upper right quadrant as I am interested in the interdependencies between various systems and how these interactions lead to path-dependent consequences. One the left side, I refer to work that has mostly assumed that linear theories suffice to guide managers in controlling the evolution of IT infrastructures. Taking a path dependence perspective, I am, however, more interested in how to understand and potentially manage complex systems by setting the right boundary conditions to cultivate evolution processes (Hanseth 2002). This focus on infrastructures and networks and their nontrivial ways of evolving is indicated by the red circle in the figure.

In the next section, I discuss work on path-dependent standards, network effects and its adoption in theories of information infrastructures.

2.2 Path Dependence in Research on Standards and Infrastructures

I begin my examination of previous work on more economic theories of IT infrastructure inertia by turning to a stream of research on information infrastructures as it closely related to traditional notions of path dependence. Along with Hanseth (2002), I define an IT infrastructure as a shared, open, evolving, standardized, and heterogeneous installed base.

Shared. IT infrastructures support or enable a wide range of activities; they are not tailored for a particular purpose; they are “shared by a larger community (or collection of users and user groups)” (Hanseth 2000:57) and cannot be split apart for different groups (except analytically).

Open. Any infrastructure is "sunk into, or is inside, other structures, social arrangements, and technologies" (Ciborra 2000:22). Infrastructures in-use incorporate various technologies and standards (Hanseth 2000).

Evolving. New infrastructures are "designed as extensions to or improvements of existing ones" – never from scratch (Hanseth and Lyytinen 2004:208). During their evolution, the established installed base strongly impacts how new components can be designed (Hanseth 2002).

Standardized. Standards play a central role within information infrastructure studies (Hanseth 2000; Monteiro et al. 2013; Pollock et al. 2007). Standard diffusion will often be driven by externalities in decisions of various actors; network effects are a core concept (Ciborra 2000:34).

Heterogeneous. Various technologies that have been implemented over several generations make up an IT infrastructure (Hanseth 2002).

Installed base. The installed base – the number of adopters or users – is central for success or failure of an infrastructure (Ciborra 2000:34). New elements in an IT infrastructure inherit the strength and limitations of the installed base.

IT infrastructures are portrayed as similar to real-world infrastructures (e.g. railway or airline networks), in contrast to investment portfolios. IT infrastructures are characterized by large "webs of externalities", complementarities, and interdependencies (Ciborra and Hanseth 2000:2). These interactions produce outcomes, which are often hard to foresee for actors due to delayed input-outcome relationships and complex causal chains (cf. Henningsson and Hanseth 2011).

Path-dependent processes are of particular importance in complex infrastructural arrangements. Hanseth (2000:66) observes that "[a]s the installed base grows [..] its development and growth becomes self-reinforcing". And, technologies which have reached a critical size of adopters are hard to abandon due to lock-in-related switching costs and coordination problems (Hanseth and Lyytinen 2004; Hanseth 2000). Due to asset specificity and high degrees of irreversibility, IT infrastructures are "sunk and sticky investments" (Ciborra 2000:34). According to this view, the successful development of infrastructures requires, "first, the creation of a self-reinforcing process, second, managing its direction" (Hanseth 2002).

2.2.1 Technical Standards and Standardization

I will now delve into the underlying notions of "standards" and "standardization". According to Weitzel et al. (2006), standardization studies can be grouped into *standard setting* and *standard diffusion* studies. Prior work on standard setting often focused on agentic processes that are important to create new paths (cf. Garud and Karnøe 2001; Garud et al. 2010). These studies figure centrally the role of different actors (consortia, industry associations, and trade groups), the formation of coalitions and the social construction of efficiency/inefficiency (Sydow et al. 2010; Windeler 2003). Studies on standard diffusion emphasize network effects in groups of adopters (Weitzel et al. 2006). In the following, I focus on standard diffusion.

According to Brunsson et al. (2012), standards carry three notable characteristics: first, standards reflect explicitly formulated and decided rules and thus differ from more implicit social norms (Brunsson et al. 2012:615). Second, standards are formally voluntary for potential adopters as they are not stipulated by hierarchical authorities of states or other organizations (cf. Liebowitz and Margolis 1996; Brunsson et al. 2012:615). The decision to comply or not is left to potential adopters. Non-compliance with the standard may however impose legitimacy problems or (social) sanctions due to "incompatibility" with the standard. Third, standards are meant for common use; having a normative character, they prescribe "what those who adopt should do and hence enable and restrict behavior" (cf. Brunsson et al. 2012:616). On the basis of this three characteristics, a standard can be defined as "*a rule for common and voluntary use, decided by one or several people or organizations"* (Brunsson et al. 2012:616).

Standardization – in the context of IT infrastructures – often takes the form of compatibility standards (cf. David and Greenstein 1990). Compatibility standards are "codified specifications about components and their relational attributes" (Garud and Kumaraswamy 1993:535) and "assure that an intermediate product or component can be successfully incorporated in a larger system compromised of closely specified inputs and outputs" (cf. David and Greenstein 1990; Widjaja 2011:6). Ensuring *compatibility* across users is a central characteristic of standards (cf. David and Greenstein 1990). Standards are "conventions or commonalities that allow actors to interact" (Liebowitz and Margolis 1996; Widjaja 2011). Thus, "compatibility may be achieved through standardization" (cf. Farrell and Saloner 1992; Widjaja 2011:6). According to Wiese (1990), compatibility harmonizes components and thus enables potential adopters to realize network effects (cf. Widjaja 2011:7). In the following, I turn to the concept of network effects.

2.2.2 Network Effects and Bandwagon Dynamics

Network effects as a concept have their root in economics (Weitzel et al. 2000, 2006). Essentially, the notion of network effects holds that a user's value connecting to a network increases with the network's size. Katz and Shapiro (1985:424) observe that "[t]he utility that a user derives from consumption of the good increases with the number of other agents consuming the good". Liebowitz and Margolis (2013) note that the term has not been restricted to increased benefits from owning a product but was applied to a variety of situations whereby an actor adopts a standard or in fact takes any action.

Research on information systems has applied the concept widely, e.g. to telephone networks (cf. Beck et al. 2008; Fuentelsaz et al. 2012; Lahiri et al. 2013), open source vs. proprietary standards (cf. Zhou et al. 2006, Cheng et al. 2010; Liu et al. 2011a), and communication standards (cf. Weitzel et al. 2006; Zhu et al. 2006). Recently, the concept gained new importance for platforms and ecosystems (Baldwin and Woodward 2008; Buxmann et al. 2011; Tiwana et al. 2010), social networking (cf. Draisbach et al. 2013), and crowdsourcing (Boudreau and Jeppesen 2012).

Traditionally, two types of network effects have been distinguished: *direct* and *indirect network effects*. Direct network effects, defined as an increasing benefit from an increasing number of actors taking the same action, are easily explained by the example of telephone networks. The utility of a user adopting a standard increases with the number of existing subscribers to that standard. Models typically take the form of $U_i = a_i + bN$ where U denotes the utility (or payoff) of agent i to adopt a technology, arising from a standalone effect a_i and the network effect bN in a network of N agents (cf. Weitzel et al. 2006:490).

Indirect network effects arise from complementarities in the consumption of goods (Beck et al. 2008:416). According to Katz and Shapiro (1985:94), "many products have little or no value in isolation but generate value when combined with others (..) These are all examples of products that are strongly complementary, although they need not be consumed in fixed proportions". Benefits may not spill over directly from one agent to others but investments can signal more complements being available in the future. This increases the (standalone) utility of the technology. The more complementary products (or services) that are available, the greater the benefit for all adopters (cf. Widjaja 2011:10). Examples include many system goods of hardware and software such as DVD players, gaming consoles, or mobile platforms (Widjaja 2011:10). Indirect network effect models typically tie the number of complementary products (and hence again the standalone utility of a technology) to the overall diffusion rate (or installed base) of a technology in the network. The positive feedback loop as depicted in Figure 5 describes the dynamics of indirect network effects: according to Katz and Shapiro (1994:94), "another situation in which consumers' coordination is vital arises when consumers must choose durable hardware, as when they purchase a device to play a new format of prerecorded music. In making such a choice, each consumer will form expectations about the availability of the software (..) In the presence of economies of scale in the production of software, the availability of software will depend on what other consumers do, which gives rise to positive feedback". Church and Gandal (1992:87f.) note that "as the number of compatible software products available for a technology increases, the value of the technology is enhanced. This leads to more hardware sales (a larger network), which increases market demand for software and enhances software profitability".

Often, direct and indirect network effects work closely together in creating bandwagon dynamics. Sterman (2000:12) builds on the Microsoft case and combines it with the dominance of Intel machines to illustrate how positive feedback influences IT infrastructure dynamics: "the larger the installed base of Microsoft software and Intel machines, the more attractive the 'Wintel' architecture became as developers sought the largest market for their software and customers sought systems compatible with most software; the more Wintel computers sold, the larger the installed base".

Similarly, Hanseth (2000:62) portrays the predominant positive feedback loop that characterizes many standard adoption processes – Microsoft Windows, the Internet, or programming languages – as shown in Figure 5: a larger installed base attracts more programmers and vendors to produce complementary products, which increases the benefit from the standard. A larger installed base with more complements also increases the credibility of the standard. Altogether, this attracts new users to the standard. This leads to more adoptions, which further increases the installed base and so forth.

Network effects and path dependence are closely related as network effects can create a tendency toward extreme diffusion outcomes where "winner-take-all" (Fichman 2004; Shapiro and Varian 2008). Alternatively, if a technology fails to develop, or if adopters group around a different platform, a “stranded” technology can result (Farrell and Saloner 1992; Fichman 2004). As a final part of this review, I turn to possibilities to get out of lock-ins from a viewpoint of research on information infrastructures.

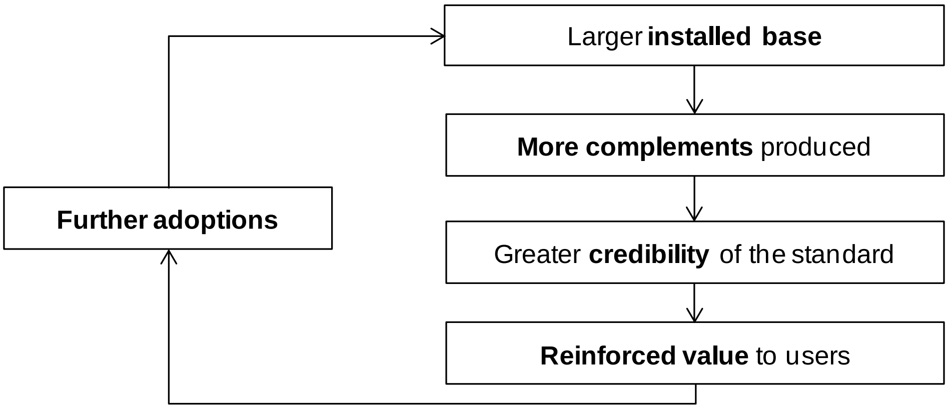

Figure 5. Standards reinforcement. Source: Grindley (1995); Hanseth (2000:62)

2.2.3 Path Breaking: Creating New Standards

Various concepts have been proposed to understand how paths can be broken (refer to Sydow et al. 2012 for an overview) such as path creation (Garud and Karnøe 2001; Garud et al. 2010), path constitution (Sydow et al. 2012), path defense or extension, unintended path dissolution, or path breaking (Sydow et al. 2009). These notions vary in the degree of taking into account “agentic” processes, path extension versus breaking, and an internal versus external perspective.

My starting point for path creation from an information infrastructure perspective is the observation that standards are often already diffused and deeply embedded in existing infrastructures (Hanseth 2000). Thus, path creation is often a question of how to get out of lock-in. The main observation is that strategies to get out of lock-in have to take into account the innovative potential of the new standard (in economic terms, the relative benefit) versus the costs of overcoming the prevailing network effects.

Consequently, to unlock paths in IT infrastructural contexts, evolutionary (1.) and revolutionary strategies (2.) have been proposed (Hanseth 2000). Evolutionary strategies (1.) aim to create a superior product providing enough incentives for actors to switch in their own interest (Hanseth 2000:68-69). The second strategy (2.) attempts to build a new, separate network and to develop gateways or other transforming devices converting between the old and the new network (Hanseth 2000). Gateways are important as they enable implementing several versions of a standard, splitting a network into simpler, manageable parts (“divide-and-conquer”), and lowering barriers that have to be overcome when switching entire networks at once (Hanseth 2002). One example for a successful gateway strategy is continuous/alternating dynamos (David and Bunn 1988). Convertibility between two different, apparently incompatible, logics, prevented a hasty decision towards one of those standards and suspended decision making until more insight into both technologies’ properties could be gained (Hanseth 2000).

In summary, these findings suggest that what remains important for establishing a new standard is considering the "underlying tension" between the forces of innovation and prevailing network effects (Hanseth 2000:68).

2.2.4 Discussion and Conclusion

Research on information infrastructures is closely related to notions of path dependence. It has drawn intensively on the (economic) concepts of standards, path dependence, and network effects to theorize inertial tendencies in complex IT infrastructural arrangements. I believe that it presents a valuable initial vantage point to build my approach upon. In the next section, I turn to other information systems research on the diffusion and adoption of innovations.

2.3 Path Dependence in Information Systems Research on Diffusion

2.3.1 Diffusion versus Adoption

A good starting point is Topi's (2014:8) observation that a perspective of diffusion and adoption has often been distinguished in research on information systems. According to Topi's literature review, work in a tradition of diffusion has been most influenced by early work on the diffusion of innovations from Rogers (1962). In contrast, work on adoption has been most affected by a study on material requirements planning (MRP) system adoption across US companies by Cooper and Zmud (1990). Essentially, the latter study argues that the processes of pre-adoption – allocating resources to require an innovation – and post-adoption – implementing the innovation in a company's IT infrastructure – are usefully distinguished as they benefit from different models explaining decision rationales within each process (Topi 2014). While pre-adoption studies may draw on models of rational decision making, post-adoption studies may, more usefully, focus on politics and organizational learning (Cooper and Zmud 1990).

Turning to the diffusion branch of the literature, I briefly introduce Roger's (1962) study on agricultural innovations and his diffusion theory. Essentially, diffusion theory argues that diffusion processes usually take time to unfold and that these processes follow typical trajectories. Most central to the theory is the diffusion curve concept; it holds that after early adopters have paved the way for the innovation, subsequently larger groups of adopters will come to join until the market finally reaches saturation whereby most willing adopters have decided to adopt. This gives the diffusion process its typical, S-shaped form where the horizontal axis depicts a measure of time and the vertical axis shows the fraction of adopters.

Examples for studies in information systems that draw on diffusion theory are Moore and Benbasat (1991) and Karahanna et al. (1999). The study by Moore and Benbasat (1991) suggests a measure to capture the perceptions of individual organizations towards adopting an IT innovation; in this context, the study is influenced strongly by Rogers' (2003) five attributes of innovation explaining their adoption – relative advantage, compatibility, complexity, trialabilty, and observability – as well as seminal work by Davis (1989) on perceived usefulness, ease of use and user technology acceptance. The instrument was adopted by Karahanna et al.'s (1999) study on pre- and post-adoption beliefs and attitudes (Topi 2014:7).

2.3.2 Spillover Effects

I now turn my attention to a recent study by Aral et al. (2009) examining the adoption of instant messaging platforms among individuals. Using a large data set on adoption behaviors, the study distinguishes two important micro-level processes driving the diffusion of the technology: influence-based contagion and homophily. I will discuss each of these processes.

Influence-based contagion – in technological contexts also termed spillover effects – designates peer influences that spill over directly from actor for actor. One may think of a disease such as influenza where the prevalence of a virus in the social neighborhood of an actor increases the propensity of that actor to also become infected (Jackson 2008b). In social settings, the underlying mechanisms are subtler. According to work from sociology and economics, the reasons for influence-based contagion include conformism (Akerlof 1997; Bala and Goyal 1998; Bernheim 1994; Bothner 2003; Burt 1987), peer pressure (Christiakis and Fowler 2011; Kirsch 2004), and learning from the experiences of others (Arthur and Lane 1993; Narduzzo and Warglien 1996; Vriend 2004). Table 1 summarizes these mechanisms.

Table 1. Description of different influence mechanisms

Mechanisms	**Description**	**Source**
Conformism	To better one’s standing through conforming to the strictures of others; social constraints	Blau (1964); Burt (1987); Bothner (2003)
Peer pressure	Formal and informal controls that are exercised on an individual by a group of others	Christiakis and Fowler (2011); Kirsch (2004)
Learning from the experience of others	Asking previous purchasers (or users) of a product about their experiences with the product they bought and subsequently used	Arthur and Lane (1993); Narduzzo and Warglien (1996); Vriend (2004)
Mimesis	Adopting others successful organizational elements when uncertain about alternatives	DiMaggio and Powell (1983); Zucker (1987)
Coercion	Formal and informal pressure on organizations by other organizations; force, persuasion, or invitations to join in collusion; sanctions	DiMaggio and Powell (1983); Zucker (1987)

From an organizational theory perspective, coercive and mimetic mechanisms have also been suggested as underlying forces to explain why behaviors spill over. Coercion designates informal and formal pressure from one organization on another organization (DiMaggio and Powell 1983). Coercion may take the form of sanctions, persuasion, or invitations to join in collusion; this has often been attributed to state authorities (DiMaggio and Powell 1983; Zucker 1987). Mimesis designates tendencies of organizations to adopt or imitate others successful elements in the face of uncertainty (Zucker 1987). Examples includes best practice transfer, employees that bring in practices from other organizations, and consultancy firms or industry trade organizations (DiMaggio and Powell 1983).

Claims of influence-based contagions have often been substantiated by demonstrating (1.) simple correlations among behaviors (e.g. adoption) of linked nodes or (2.) temporal clustering in the timing of behavior (e.g. adoption) among linked agents (Aral et al. 2009).

A number of studies in information system research have utilized these concepts. Linking coercion with standard diffusion, a study by Bala and Venkatesh (2007) finds that influence mechanisms were important to explain the assimilation of business process standards particularly for non-dominant firms. Kirsch (2004) discusses peer pressure as a mechanism in global software projects to exhibit control. A study by Singh and Phelps (2013) examines how prior adopters of open source software licenses socially influence the susceptibility of subsequent actors to adopt a particular license type. Most importantly, the study finds that the interpersonal network is most decisive in determining the choice of a license type.

Another process that has been suggested in driving diffusion is homophily. Essentially, homophily denotes a correlation through sorting. Technically, it can be understood as a process in which linked agents that share certain "demographic, technological, behavioral, and biological similarities" become increasingly similar in other attributes, for instance the technologies they choose, over time (Jackson 2008b; Aral et al. 2009:21544). Based on this distinction, Aral et al.'s (2009) large-scale quasi experiment treat instant messaging platform adopters as either peer-influenced or homophile. The study found that about 50% of the adoption rate could was explained by homophily whereas the other half was explained by influence-based contagion (Aral et al. 2009).

2.3.3 Diffusion and Path Dependence

The intersection of diffusion research and path dependence goes as far back as Arthur's (1989) seminal work on path dependence. Arthur's model of path dependence and increasing returns conceptualizes path dependence in markets of technology adopters and captures how individual level technology adoption interacts with population-level diffusion outcomes in shaping path-dependent trajectories towards one of several competing technological innovations. The main concepts of path dependence, salient already in this article, are contingencies towards early events, self-reinforcing mechanisms, and lock-in (Arthur 1989; Sydow et al. 2009). The concept of self-reinforcement is particularly strongly interwoven with diffusion dynamics as new adopters, entering the market sequentially, potentially increase the population-level adoption rate of a dominant technology, with their decision influencing subsequent adopters' decisions (Shapiro and Varian 2008). I believe that this underlying core idea – understanding path dependence as a problem of standard diffusion – has lost little appeal but was largely forgotten thereafter.

Recent work by Greve and Seidel (2014) has again linked the concepts of diffusion and path dependence. Focusing on the adoption of aircraft models among airlines, the study focused particularly on how early events shape the subsequent diffusion process as well as how peer influences – designated in the article as social selection mechanisms – drive the following diffusion process of the innovation. Essentially, the article argues that a delay in the production start of one aircraft was decisive as social selection mechanisms – that worked in the meantime – have predetermined the eventual outcome of the adoption process. I believe this result is important as it highlights the critical importance of individual level interactions among agents in studying path-building processes.

2.3.4 Discussion and Conclusion

Turning in conclusion to implications for my work, I believe that the studies by Aral et al. (2009) and Greve and Seidel (2014) demonstrate clearly that it is necessary to go beyond the network size as the primary variable to explain diffusion outcomes and to take into account spillover effects among individual agents. Influence-based contagion, as well as homophily, are important processes in understanding how technology trajectories enfold.

2.4 Network Analysis as Theoretical Foundation

Networks gain importance as a theoretical perspective[6] to understand diverse phenomena such as passenger traffic planning, epidemics, technology adoption, or innovation diffusion (Borgatti et al. 2009; Brockmann and Helbing 2013; Jackson 2008b; Kliewer and Suhl 2011; Valente 2012). I turn to the examples of organizational IT infrastructures and airline distribution IT to show how a network perspective can usefully serve to study path building and path breaking.

2.4.1 Organizational IT Infrastructures as Networks

A network perspective serves useful to understand path dependence in organizational IT infrastructures as it supports (*a*) visualization and analysis of complex interdependencies, and (*b*) modeling of the processes governing their evolution.

Networks consist of a set of nodes and edges. I suggest applications – enterprise resource planning systems as well as autonomous billing modules based upon MS Access – to represent nodes interacting with each other. In network analysis terminology, I define them as nodes. To create a network for viable analysis, one needs to operationalize these interactions. One may turn to a bipartite (also called a two-mode) network (Wasserman and Faust 1994). In such network, an edge between two applications may be constructed if both are used in the same business process. Hence, we would need to assess relevant processes. Many IT systems are highly independent of central surveillance (Ciborra and Hanseth 2000). Such systems will not contribute primarily to standardized logics. Instead of assessing systems by using centrally defined processes, I thus find a one-mode network based upon actual information flows, in forms of integrated interfaces, superior for my analysis. In such a network, edges materialize in implemented and actually used interfaces (e.g. file transfers, web services) between two systems (Dreyfus and Iyer 2008).

[6] Provan et al. (2007:481f.), in an overview article on interorganizational networks, distinguish between networks as a perspective and as a form of governance. I position my work in the former literature as I am concerned with models, tools, and methods capturing the "relational embeddedness" of behaviors.

2.4.2 Global Airline Distribution IT as a Network

The transportation system is another useful example to study network phenomena (Barrat et al. 2004; Brockmann and Helbing 2013). The underlying transmission network, a large fixed investment, creates incentives for companies to collaborate (e.g. via interlining, codesharing, or through traffic), because working together can create synergies from a higher utilization of each individual company's inventory (Puffert 2009:248). Higher capacity utilization – often equated with higher revenues – benefits from interorganizational sales systems that combine offers from different, distant transport companies, because users (e.g. travel agents) may be incapable, unwilling, or too slow searching offers from a large number of possible connections.

The examples of the airline and railway industries suggest that different IT-based collaboration patterns (i.e. centralized, or decentralized) can arise in passenger transport (Schulz et al. 1996). Drawing on airline distribution as an example, the product's transnational character creates incentives to build global distribution infrastructures. Traditionally, only centralized infrastructures provided sufficient computing power (Copeland and McKenney 1988). These infrastructures were costly to build and maintain, which created incentives for airlines to share them (Copeland and McKenney 1988).

To see how a network perspective can add our understanding on path creation in airline distribution, consider the following scenario. Let us assume we can model interactions between airlines as a network that indicates who interacts with whom. One may think of n airlines linked through codesharing agreements. To keep things simple at this point, let us presume that airlines are either linked or not, so that we can ignore the fact that some organizations might involve more frequent or intense interactions than others. Consider now the introduction of a new standard (e.g. a technical format for distribution). Airlines can either adopt the standard or not. Adoption is driven by spillover effects from one individual carrier to another as each airline will be more willing to standardize if their partners also do so. Let us also presume that airlines face different switching costs that operationalize in different threshold values to adopt. We can then ask: under which circumstances does the new standard diffuse to a nontrivial fraction of airlines? Will there be a tipping point above which all airlines adopt?

2.4.3 Discussion and Conclusion

In a celebrated essay, Hanseth (2002) suggests that information systems research should move from "systems and tools to networks and infrastructures". The examples of global airline distribution IT and organizational IT infrastructures show how a network perspective can inform "how to study, make sense and intervene in complex infrastructural arrangements" (Hanseth and Lyytinen 2004). I thus draw on network analysis as theoretical foundation. The next section introduces formal models clarifying my conception of path dependence and standard diffusion.

2.5 Selected Formal Models

I discuss selected formal models of path dependence and standard diffusion in networks. From a small set of models on IT infrastructure path dependence as well as a broader range of models on standard and innovation diffusion, the subsequent models were selected by (a) their perceived usefulness to model important processes within the problem instances, and (b) their conceptual compatibility with path dependence models, especially the one presented in Arthur (1989).

2.5.1 Basic Definitions

Drawing on work by Page (2006), path dependence is defined formally and distinguished from other dynamic processes. My starting point is a dynamic process with discrete time intervals indexed by integers, $t = 1, 2, 3\ldots$[7]. I denote the outcome at time t as x_t. A history at time T, h_T is the combination of all outcomes x_T up to time $T - 1$. A **history-dependent** dynamic process has an outcome function G_t that maps the current history into the next outcome (Page 2006:92). As shown in Equation 2.1, the outcome generated by a dynamic process is then:

$$x_{t+1} = G_t\ (h_t) \tag{2.1}$$

In Bernoulli processes the probability of outcomes in the next period is independent of past outcomes (Page 2006:94). These and similar processes will not be of further interest.

The outcome function can change over time, so it is indexed by t. For path-dependent processes, the function G_t will be stochastic[8]. Thus, it creates a probability distribution over outcomes (Page 2006). In the following, I am interested in processes limiting the long-run distribution over outcomes. These processes are called **equilibrium-dependent (**Page 2006).

In some cases, it is possible to partition the space of all histories into a finite number of sets $\{s_1,\ldots,s_N\}$ such that the outcome function at each moment in time depends only on the set to which the current history belongs. These sets are called *states* (Page 2006:94). Think of the number of red and blue balls in an urn, the members of a population, or adopters of a technology.

A state transition rule, T, maps the current state s_t and (possibly) the current outcomes x_t into the next period's state (Page 2006:95). This can be written as $s_{t+1}=T(s_t,x_t)$. The state transition rule depends only on finite states. A process is **state-dependent** if the outcome in any period depends only upon the state of the process at that time. It can be written as follows:

$$x_{t+1} = G_t\ (s_t) \quad \text{where } s_{t+1} = T(s_t,x_t) \tag{2.2}$$

In simple Markovian machines the state transition rule T remains the same in every period. This property is called stationarity (Page 2006:95). It implies that $G_t=G$ for all time periods t.

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[7] This is called a discrete time process. Refer to Ashby (1956:9) for a discussion of continuous versus discrete change in machines/systems. See Law (2007:6) and Law (2007:78f.) for a discussion of fixed-increment time advance as a special case of discrete-event simulation models.

[8] A discussion of deterministic versus stochastic simulation models is given by (Law 2007:6). According to his definition, "if a simulation model does not contain any probabilistic (i.e. random) components, it is called *deterministic*". Otherwise, it is called *stochastic*. According to Vergne and Durand (2010:741), a path-dependent process is necessarily a stochastic process.

To understand this more clearly, imagine a simple model of a large number of insects living in a pond (cf. Ashby 1956:167f.). An outside oberver sees only the sets of insects living on the sand bank (*B*), in the water (*W*), and under the pepples (*P*). If their values are *B*, *W*, and *P* in one moment, then they change to *B*' and so forth in the next. Of the insects in the water, three-quarters will change over to the bank, while a quarter will go to the pebbles. Further, one-eighth of the insects from the pebbles go usually to the bank. In general, the three populations will change according to the state transition probabilities as described in Table 2.

Table 2. *Sample Markov process transition probabilities. Source: Ashby (1956:168)*

↓	*B*	*W*	*P*
B	1/4	3/4	1/8
W	3/4	0	3/4
P	0	1/4	1/8

Imagine in the following that we start with a 100 insects in the pebbles and watch the subsequent dynamics. On average only 12.5 would remain there, the remainder would go to the bank (12.5 also) and to the water (75). The sets tend, through dying oscillations, to a state of equilibrium, at (44.9, 42.9, 12.2) as shown in Figure 6, at which the system remains indefinately. Refer to code example oS1 in the online supplements for a Netlogo implementation of the Marchov chain model. It shows that the steady state equilibrium is not necessily unchanging as members of the population continue to move incessantly.

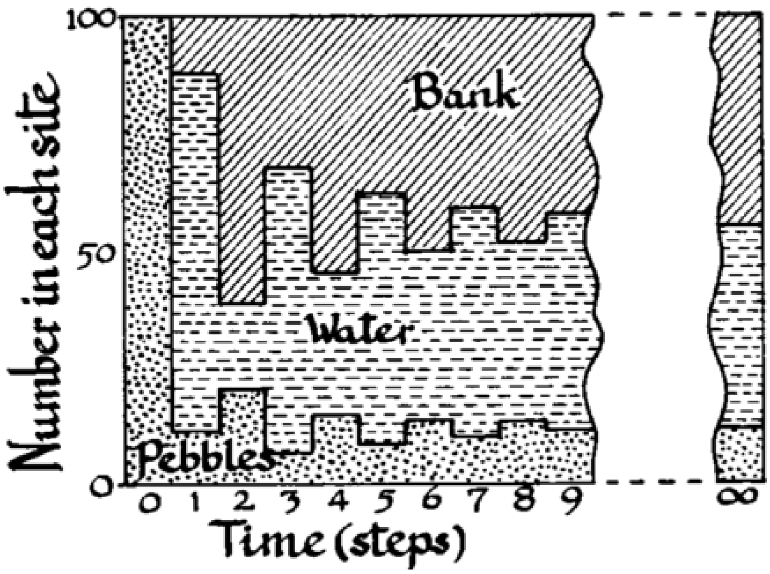

Figure 6. *Diffusion graph in Markov chain example. Source: Ashby (1956:168)*

Both path-dependent processes and Marchovian machines can be *determinate*, resulting in a steady-state equilibrium. I distinguish path-dependent processes from other sorts of state-dependent processes, such as Marchovian machines, by showing that path-dependent processes are **non-stationary** and **non-ergodic**. Drawing on work by Page (2006), I illustrate these two properties by turning to simple ball and urn models (Arthur 1994).

2.5.2 Urn Models

Urn models consist of a collection of various colored balls placed in an urn. In accordance with Page (2006), I assume balls with two colors: maroon, which I denote by M, and brown, which I denote by B. In each period, a ball is selected from the urn and, depending on the color of the ball selected, other balls may be added or removed from the urn. The selection of the ball plays the role of the outcome function (Page 2006). Because the ball is selected randomly, the probability of an outcome depends on the composition of the urn: how many balls of each color it contains. In each period, a ball is selected and returned to the urn, and another ball is added to the urn of the same color as the selected ball. This portrays the phenomenon of increasing returns as described by David (1985) and Arthur (1994).

Polya Process. "*Initially, $M = B = 1$. In any period, if a brown (resp. a maroon) ball is selected then it is put back in the urn together with an additional ball of the same color.*" (Page 2006:98)

The Polya Process is equilibrium-dependent and can converge to *any* ratio of maroon and brown balls (Page 2006:98). Depending upon the history of outcomes the urn could eventually contain 80% maroon balls and 20% brown balls, or it could contain 63% maroon balls and 37% brown balls. At some point, the urn contains enough balls that the ratio converges, and balls continue to be selected in those proportions. Figure 7 shows a simple example. Refer to code example oS2 in the online supplements for an n-color implementation of the Polya Process.

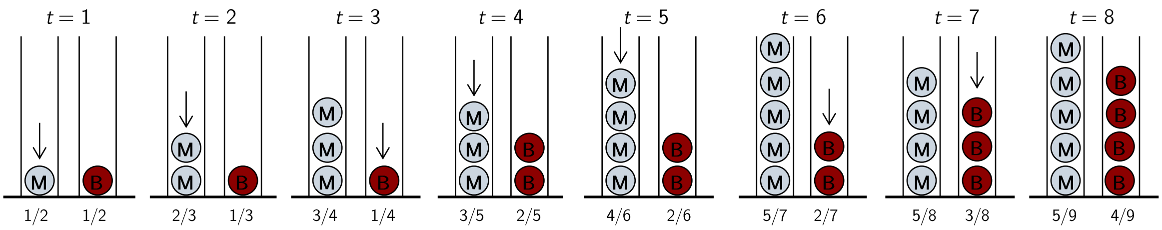

Figure 7. *Simple example for one run of the Polya Process*

With this example in mind, one can define a process as **path-dependent** if the outcome in any period depends on the set of outcomes and opportunities that arose in its history. According to Page (2006:97), a path-dependent process can hence be written as

$$x_{t+1} = G_t\ (\{h_t\}) \qquad \text{with } s_{t+1} = T(s_t, x_t) \tag{2.3}$$

where $\{h_t\}$ denotes the set of outcomes up to time t. A stronger condition of path dependence where the particular sequence of events (the ordering) also matters would define $x_{t+1} = G_t\ (h_t)$. This implies that changing the order of x_1 and x_2 could change the outcome produced by G_t. I stick to the basic definition in Equation 2.3 and I will only refer to the stronger condition if mentioned explicitly.

Consistent with Page (2006:99), I define a dynamic process as generating **increasing returns** if an outcome of any type in period t increases the probability of producing that outcome in the next period.

Given this definition, the Polya Process satisfies increasing returns. It is thus possible for an urn process to exhibit increasing returns and to generate multiple equilibria.That does not mean that all processes with increasing returns produce multiple equilibria, nor does it imply that all process that generate multiple equilibria satisfy increasing returns. In fact, no logical implication exists in either direction (Page 2006:100).

To show why path-dependent processes don't have to go together with increasing returns, I refer to a modified Polya process where we add two more colors (Red and Green) (Page 2006:100).

Modified Polya Process. "*Initially, we start with M = B = R = G = 1. If a maroon ball is selected, a red ball is added to the urn. If a green ball is selected, a brown ball is added to the urn. And if a brown ball is selected, a green ball is added to the urn.*" (Page 2006:100)

Pick R →Add M
Pick M →Add R
Pick G →Add B
Pick B →Add G

To show that this process exhibits equilibrium dependence, paint the red balls maroon and the green balls brown. Doing so creates the Polya Process which was previously shown to be equilibrium-dependent (Page 2006:100). The modified Polya Process does not, however, satisfy increasing returns. In any given period, choosing any color ball decreases the probability of picking that ball in the next period. Figure 8 shows a simple example with t = 4 periods that shows this quite clearly. From this perspective, increasing returns are not necessary for equilibrium dependence (Page 2006:100). One may, however, understand the Modified Polya Process as an example where complementarities exist, because red balls create an environment favorable for maroon outcomes in the future (Page 2006:100).

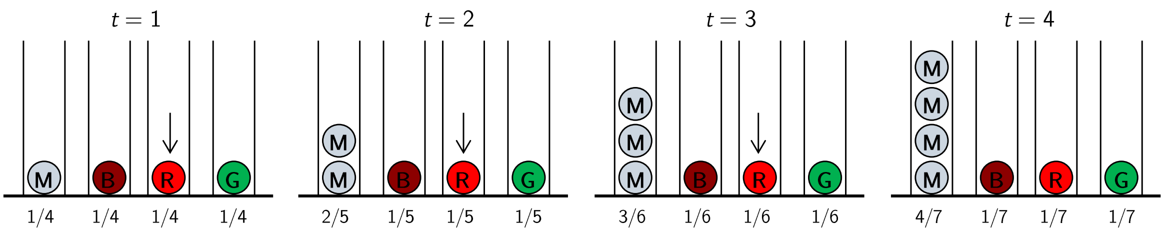

Figure 8. *One sample run of the modified Polya Process over four periods*

To show why increasing returns are not sufficient for path dependence, imagine a biased Polya process where brown balls have an advantage (Page 2006:101).

Biased Polya Process. "*Initially, M = 1 and B = 2. In each period a ball is selected. If a maroon ball is selected, it is put back in the urn together with another maroon ball and another brown ball. If a brown ball is selected in period t, it is put back in the urn together with 2t additional brown balls.*" (Page 2006:101)

Eventually, the proportion of brown balls in the urn converges to 100 percent, so this process generates one unique equilibrium. We can see that selecting a brown ball satisfies increasing returns. Maroon balls also satisfy increasing returns. If we select a maroon ball, then the probability of selecting a maroon ball in the next period also increases. Thus, a process may generate increasing returns but will still be ergodic (not path-dependent).

This brings us to a formal definition of **non-ergocity** (cf. Arthur 1989). For path-dependent processes, we request that two samples from the observer's set of possible historical events $\{t_i\}$ and $\{t_{i'}\}$, with corresponding time paths $\{x_n\}$ and $\{x_{n'}\}$ are *un*equal with probability one, as n→∞ (Arthur 1989:128). Hence, path-dependent processes can exhibit multiple equilibria and it is not predictable ex-ante which of several possible outcomes will comes to dominate. The Biased Polya process is ergodic (not path-dependent) as different sequences of historical events always lead to the same market outcome with probability one. In contrast, the Polya process is non-ergodic.

Imagine as a last example a **Balancing process** where a ball is selected from an urn, and depending on the color of the ball, the ball is put back in an urn together with an additional ball of the opposite color (Page 2006:99). Refer again to code example oS2 in the online supplements for an implementation of the model. To see why the Balancing process cannot create multiple equilibria imagine an urn with a large number of balls, 60% of which are maroon and 40% of which are brown. From that point onward, maroon balls would be more likely to be selected. Selecting these maroon balls would add brown balls to the urn, increasing the proportion of brown balls above 40%. The Balancing process always converges to equal fractions of maroon and brown balls. The Balancing process is hence ergodic (not path-dependent). In fact, the Balancing process is a prime example for a process under negative feedback as the selection procedure punishes a given color until it returns to the base level.

2.5.3 Arthur's (1989) Model of Path Dependence and Extensions

I now turn to an important model building on urn models: Arthur's (1989) model of competing technologies, path dependence and increasing returns. While interaction patterns between agents are not explicitly captured, the model serves as a useful starting point, combining increasing returns and path dependence in a two-tier model.

The base model works as follows: imagine a market of technology adopters choosing between two competing technologies as Berkeley Unix (B) and Microsoft (M). Sticking to the terminology introduced above, we can think of this market as an urn with two sets of balls. We color Berkeley Unix adopters *brown (B)* and Microsoft adopters *maroon (M)*. In each period, one new potential adopter (ball) enters and selects a technology (his or her color) with the highest payoff according to the payoff function U as depicted in Table 3.

Table 3. Network effects in Arthur's model of path dependence

Brown (Berkley Unix)	$U_b = r\ n_b$
Maroon (Microsoft)	$U_m = r\ n_m$

where n_b is the fration of brown balls already in the urn (the number of Berkley Unix adopters) and n_m is the fraction of maroon balls in the urn (the number of Microsoft adopters). Let r be the network multiplier. If r is non-negative, it indicates the strength of the increasing returns (otherwise, the model yields constant or negative returns). If the agent selects Microsoft (a maroon ball), the agent is added to the installed base of the technology (the drawn ball is put back in the urn together with another maroon ball). If a brown ball is selected in period *t*, it is put back into the urn together with one additional brown ball.

To complicate matters, imagine now we had not only two sets of balls but also two sets of agents (*R*-agents and *S*-agents) differing just by one attribute: the *preferences* towards brown and maroon balls. The base preferences – one could think of a standalone utility of the technology for the agent – is denoted as a_R and b_R for *R*-agents, while they are a_S and b_S for *S*-agents. These preferences are real-valued and non-negative. For *R*-agents, it is assumed that $a_R > b_R$ and for *S*-agents it is assumed that $b_S > a_S$. *R*-agents prefer brown balls while *S*-agents will be happier if they select maroon balls. Combining these base preferences with influences from the network, we end with the agent's payoff functions as depicted in Table 4.

Table 4. Payoff functions of agents in Arthur's simple model of path dependence

	Brown (Berkeley Unix)	Maroon (Microsoft)
R-agent	$a_R + r\ n_b$	$b_R + r\ n_m$
S-agent	$a_S + s\ n_b$	$b_S + s\ n_m$

To remain completely in our urn world, imagine we flag new balls by the type of agent (*R*-agents get a flag that they are from *Rostock* and prefer *Berkeley Unix* while *S*-agents are from *Stuttgart* and prefer *Microsoft*). Both flags (agent-types) are equally likely. The agent from *Rostock* has base preferences – think of them as the heights of two hills – of a_R for Berkley Unix (brown balls) and to b_R for Microsoft (maroon balls), e.g. 15 cm and 10 cm (as a_R is always larger than b_R). People from *Rostock* have a natural inclination towards *Berkley Unix*. Each ball in the urn (each agent in the population) adds an additional height of 1 cm to the hilltop depending on the agent's technology choice (color), which can be stretched by *r* (e.g. we assume the balls are of rubber and will be doubled as *r* equals 2). The new ball is now colored by the color of the higher stack. If the urn now held 5 brown balls and 6 maroon balls, the agent's Berkley Unix (brown) hill piles up to 25 cm, while the Microsoft (maroon) hill piles up to 22 cm. Thus, in addition to all existing balls, another agent turns to Berkley Unix (a brown ball is added to the urn). One can show that an agent from Rostock (*R*-agent) would never choose Berkley Unix (a brown ball) again, if the process pushes Microsoft (maroon balls) far enough ahead such that $n_b - n_m < (b_R - a_R) / r$. To understand this absorbing barrier (cf. Figure 9), imagine that the process randomly samples three agents from Stuttgart (*S*-agents) in a row, all of which turn to *Microsoft* (maroon balls). The new distribution over outcomes is now 5 people that have selected *Berkley Unix* (brown balls) and 8 people have selected *Microsoft* (maroon balls). The next *agent from Rostock* entering the scene will now face a situation where the height of the *Berkley* (brown) staple is 15 cm plus 5 x 2cm, which equals 25 cm. The *Microsoft* (maroon) staple has in contrast grown to 10 cm plus 8 x 2 cm, which equals 26 cm. Hence, the new agent will select Microsoft (turns to a brown ball) despite differing base preferences. As this is also true (and gets even worse) for all subsequent agents from Rostock, the battle is over and the fraction of Microsoft adopters (maroon balls) will increase constantly. The same would be true if $n_b - n_m > (b_S - a_S) / s$ for S-agents. Consequently, brown balls would come to populate the urn more and more. The urn converges upon a steady-state equilibrium that equals the long run distribution over outcomes (1.0 0.0) or (0.0 1.0).

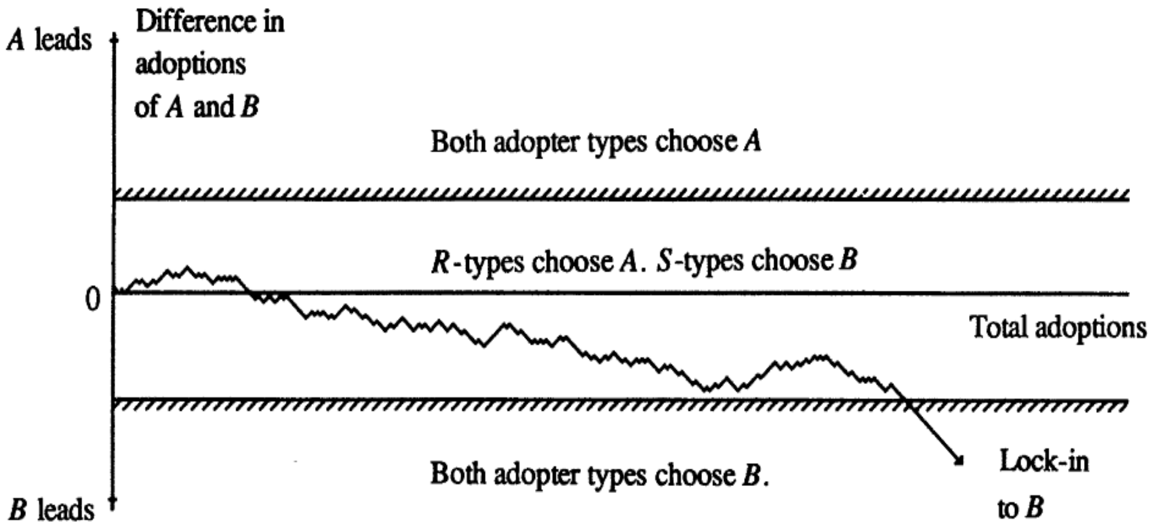

Figure 9. Barriers in Arthur's path dependence model. Source: Arthur (1989:120)

The model has different interesting features. Firstly, it cannot be foreseen ex-ante which of the two sets of balls will eventually come to dominate. The process is non-ergodic (path-dependent) and equilibrium-dependent. One set of balls will always come to dominate but a random walk determines which set of colors will eventually win. Secondly, once the absorbing barrier is passed, a stochastic process turns into a qualitatively-different kind of process: a deterministic process in the form of a steady-state equilibrium (Lamberson and Page 2012:192). The height of the absorbing barrier thereby simply depends on the size of the network effects (r and s) and the initial threshold of base preferences towards balls (a_R and b_R, or a_S and b_S respectively): the ratio of base preferences to network effects. It is interesting to note that in a lock-in situation half of the population – at the limit – switches to a color which conflicts with their natural inclination. Abstracting away the limitations of two agents and two technologies, the model generalizes to the payoff function as depicted in Table 5.

Table 5. Payoff functions of agents in a generalization of Arthur's model

	k^{th} technology
i^{th}-agent	$a_{ik} + b_i\, n_k$

In Table 5, we denote different sets of the agents (e.g. R-agents, S-agents) by the index i and the set of technologies by k. Standalone utilities vary across types of agents *and* technologies while each agent type enjoys network effects (b_i) in equal height for each of the k technologies.

Relaxing the assumption of identical network effects across agent groups yields qualitatively different results; it results in a biased Polya Process where one technology comes to dominate if the absorbing barrier for one technology is not yet passed (Leydesdorff and van den Besselaar 2000:9f.). This opens up the space for “lock outs” (Leydesdorff and van den Besselaar 2000).

The model has informed thousands of studies on standard diffusion, platform competition and path dependence in technical and organizational contexts. It also informed many works in the economics of IS field and especially on the software industry (Buxmann et al. 2011). Both, (*a*) formal and (*b*) quantitative-empirical approaches have been employed to apply and extend the model. I discuss them briefly.

Formal approaches (*a*) – in more economic work on information systems – pick up the topics of platform competition for gaming consoles (Liu et al. 2011a), software platforms (Cheng et al. 2010; Lee and Mendelson 2007; Zhou et al. 2006), telecommunication markets (Beck et al. 2008), or social networking platforms (Draisbach et al. 2013). Researchers have often suggested formal-analytical models drawing on the concepts of increasing returns or lock-in. Simulations have been used less frequently in work drawing on Arthur’s model. Exceptions are Weitzel et al. (2006), Beck et al. (2008), Draisbach et al. (2012). Beyond its direct application in information systems, prior approaches apply Arthur’s model in fields as diverse as innovation management (Frenken et al. 2012; Leydesdorff and van den Besselaar 2000; Leydesdorff 2000), organizational rule adoption (Petermann et al. 2012), or institutional change (Crouch and Farrell 2004).

Quantitative-empirical approaches (*b*) often estimate network effect strength or transition matrices in empirical markets, e.g. for Microsoft Windows and Linux operating systems (Economides and Katsamakas 2006), the pre-packaged software industry (Lee et al. 2010), interorganizational standards (Zhu et al. 2006) or the telecommunications industry (Fuentelsaz et al. 2012). For reasons of relevance, I turn my subsequent attention to simulation-based approaches.

Leydesdorff (2000): Agents in Interacting Selection Environments

Leydesdorff (2000) extends Arthur’s model of path dependence by bringing in multiple selection environments. One may think of these selection contexts as market segments, niches, regions, nations and so forth. From an evolutionary perspective (Nelson and Winter 1982), it is argued that market segments could shield a new technology to reach a critical mass and “lock out” users to leave an existing path. Interaction effects could, however, also reinforce a path even more.

For two selection environments their model is set up as follows: R and S-type adopters arrive randomly as before and will additionally be assigned to market segments uniformly at random. The agents’ base preferences and network effects coincide in these two markets (C and D) differing across agent types (analog to Table 4). The authors then assess the four combinations of markets and technologies (AC, AD, BC or BD) as depicted in Table 6. Given this basic model, the authors find (separate) lock-ins in both market segments. Both markets often tip towards different technologies as markets evolve independently.

Table 6. *Agents in different selection environments. Source: Leydesdorff (2000:248)*

	Technology *A*	Technology *B*
Market *C*	*AC*	*BC*
Market *D*	*AD*	*BD*

Next, the model introduces a coupling mechanism between technologies and market segments. In particular, network effects (r and s, cf. Table 4) and market segments interact positively. The network effect is separated across markets; for example it becomes r_1 and r_2 for R-agents. Under these conditions, each adoption of one technology in one market now increases the strength of the network effect of the given technology in the given market. The network effect for R-agents towards technology A in market C will for instance increase by $r_1 = r_1 * 1.001$. The remaining setup is unchanged; if a technology is selected in one market, the number of adopters is increased by one agent and so forth.

The model shows that the positive interaction of two stochastic processes enhances the lock-in (Leydesdorff 2000:250). The system is expected to lock in to one of the four options. For three selection contexts (a "triple helix"), more complex outcomes occur (Leydesdorff 2000:251).

Altogether, the model adds to our understanding by bringing in multiple selection contexts, which may be re-conceptualized as different segments of the airline industry. Within this setting one market segment is the market of airlines adopting (booking-class versus other) technologies and another market is the market of travel agents. The model by Leydesdorff (2000) paves the way to modeling the interactions between both segments and hints at possible path reinforcements.

Draisbach et al. (2012, 2013): Incorporating the Network Structure

I turn to a model by Draisbach et al. (2012, 2013) as it incorporates the network structure more explicitly. Drawing on the strategic decision-logic from Arthur's model in Table 4, they assume that new agents will not be influenced by all other agents but only by a number of direct partners. Drawing on social networks as an example, the authors highlight the need for incorporating direct influences from friends or peers for technology adoption.

To understand the model, imagine a network $N(g)$ described by a real-valued adjacency matrix n x n. The network is unweighted, undirected and simple. The network is static, which means that the number of n nodes remains constant over time. The authors create a network with a certain structure (e.g. a random network) and assign agents to nodes – one may imagine slots filled by new agents – uniformly at random. Each new agent than selects which ball it should select (turn into) based on the calculus as depicted in Table 7.

Table 7. *Modified payoff functions. Source: adapted from Draisbach et al. (2012:5)*

	brown	maroon
R-agent	$a_R + r\ \Sigma_{i \in N(j)} t_{b,i}$	$b_R + r\ \Sigma_{i \in N(j)} t_{m,i}$
S-agent	$a_S + s\ \Sigma_{i \in N(j)} t_{b,i}$	$b_S + s\ \Sigma_{i \in N(j)} t_{b,i}$

Let t be a binary (dummy) variable, which takes a value of 1 if node j is of the color which agent i is currently assessing (e.g. brown), and 0 otherwise. Agent i thereby assesses all direct neighbors $j_1,..j_n$ in a radius of one step. After the agent has chosen a color, the game is continued and another agent is assigned to the network uniformly at random and so on.

The authors are concerned with the number of agents for which the eventual decision conflicts with their base preferences, so-called “individual lock-ins” (Draisbach et al. 2012:8). By the means of simulation, they find that the number of individual lock-ins increases with the size of the network effects (r and s), which is not surprising. The upper boundary for the number of individual lock-ins is half of the population (as in the Arthur model). For different random networks they show that the link probability affects the extent of individual lock-ins: if a network is densest, the number of individual lock-ins is highest. What is interesting is that there is almost no difference between full density networks (where the link probability is one) and networks with a link probability of 0.6. In sparser networks, the curve of “individual lock-ins” for increasing network effects is smoother and fewer “individual lock-ins” can be observed.

2.5.4 Externalities Model by Page (2006)

Page (2006) presents another class of models on path dependence, which are decision-theoretic in nature. These models set themselves apart from urn-type models by (*i*) being sensitive to the (specific) sequence of events and (*ii*) considering externalities as a (broader) class of mechanisms that create path dependence. By externalities, Page (2006) refers to – positive as well as negative – spillovers between activities or, in general, interdependencies in the choices of actors.

An example is presented in Page (2014). Consider in connection a portfolio of projects described by a vector $\{ABCDE\}$. Each of these projects has a value of 10 and creates externalities as depicted in Table 8. The intersecting cell, A x A, depicts the (isolated) value of 10. The other cells (e.g. A x B) show the size of externalities between projects, e.g. if project A is conducted it spills over negatively to project B and causes a potential damage of 20 units to the value of project B. This externality is, however, only realized if both projects are performed.

Based on this example, Page argues that the specific sequences of events matters for the set of outcomes, which will eventually result. Consider that the firm started by assessing project A and its potential spillovers. Combining projects AB would not lead to a positive payoff as the firm gets 10 for A, 10 for B, but both projects will conflict each other and produce a negative externality of -20 (10 + 10 - 20 = 0). Combining project A and C, in contrast, yields a positive payoff: the firm gets 10 for A, 10 for C, which is increased by a surplus of 5 as both projects complement each other. Taking into consideration project D also, the firm finds an additional spillover of -10 from doing AD together and no effect of C on D, which results in a total situation of 10 + 10 + 5 + 10 (for D) – 10 (for AD) + 0 (for CD), which equals 0. Hence, the firm ends up doing D in addition to AC or not. Altogether, the firm which started with project A might end up doing AC *or* ACD. Imagine now the firm initially started with project B. As I have shown earlier, it would not combine AB as there is no net value. Combining BC would also yield little value as there is a negative spillover of -10. Doing BD, in contrast, would be highly beneficial indicated by a bonus of 30. Altogether, the firm finds itself in a very different position based on the initial conditions – which activities they have put forward – but also the type of activities they have selected along the path. With externalities, earlier projects can constrain or influence later projects.

Table 8. Example matrix of project externalities. Source: based on Page (2014)

↓	A	B	C	D	E
A	10				
B	-20	10			
C	5	-10	10		
D	-10	30	0	10	
E	10	-10	0	0	10

Think of the model's outcome x_t as sets of projects (as defined formally in chapter 2.5.1) and think of different decision rules T. We used a decision rule where a project was approved if its expected value was larger than zero. A decision rule is now *history-dependent* if there exists a reordering – which is defined as a permutation of a sequence of projects – of some finite set of projects that makes a different set of approved projects beneficial.

The model is sensitive to the specific sequence of events. Consider in this connection the Arthur model as introduced in chapter 2.5.3. Let's assume, we would set the standalone utilities to zero. Imagine there are two brown (Berkley Unix) balls (adopters) and four maroon (Microsoft) balls (adopters). The distribution over outcomes is (1/3, 2/3). The next agent entering the scene will calculate utilities irrespectively of whether the prior sequence has been *R-R-R-R-B-B, R-R-R-B-B-R, R-R-B-B-R-R* or so forth. A decision maker in the externalities model, by contrast, assesses chunks of projects resulting maybe in different orderings based on the starting point.

2.5.5 Models on Standardization Problems

I turn to a class of models on standardization problems (Buxmann et al. 1999; Domschke and Wagner 2005) originating in economic work on standardization (e.g. David and Greenstein 1990; Farrell and Saloner 1992; Besen and Farrell 1994) and transaction costs (Williamson 1981). This class of models is important as it links strategic agents with a network perspective. Most of them are, however, concerned with central optimization problems.

The standardization problem conceptualizes standardization as a process in which agents balance their utility when standardizing against standardization costs (cf. Buxmann et al. 1999; Weitzel et al. 2000). The authors argue that standardization benefits often arise from compatibility with potential standardization partners (cf. chapter 2.2.1). One may think of the introduction of an EDI document exchange standard where standardization benefits result from reductions of postal charges or eases in transaction speed. Similarly, an ERP implementation may reduce interface and personnel costs (Buxmann et al. 2011:40f.). On the other hand, implementing a standard causes standardization costs. These arise from implementing, licensing, and integrating the standard (Buxmann et al. 2011:41).

Similar to Arthur's model of path dependence, standardization models thereby assume that an agent's utility decomposes to a standalone utility and a network effect (Buxmann et al. 2011:40). Regarding the latter, the authors observe that an agent *i*'s utility from standardization depends on decisions by $j_1,,j_n$ related agents. The standardization problem then arises from the interdependencies in agents' decisions (cf. Besen and Farrell 1994).

Drawing on graph optimization, the (basic) standardization problem is formulated as a discrete optimization problem (cf. Domschke and Wagner 2005). According to the formulation by Buxmann et al. (2011:43), the objective is to find an optimal balance between standardization costs and benefits, which is achieved by maximizing the standardization net benefit F for the decision variable x according to Equation 2.4 as follows

$$max\ F(x) = \sum_{i=1}^{n} (b_i - a_i)x_i - \sum_{i=1}^{n} \sum_{\substack{i=1 \\ j \neq i}}^{n} c_{ij}(1 - x_i\, x_j) \tag{2.4}$$

$$s.t. \qquad x_i \in \{0,1\}$$

where x_i denotes a binary variable that takes the value of '1' if agent i standardizes. Only in this case the base utility a_i is realized and standardization costs K_i accrue. Information costs c_{ij} – which can be reduced by standardization and which can hence be interpreted as (economic) network utilities – accrue if and only if both (potential) standardization partners i and j standardize, shown by binary variables x_i and x_j. The linear program attempts to maximize the difference between standalone utilities and network utilities for all n agents in the network.

To understand the standardization problem, imagine a firm assessing a new document standard. The central observer, e.g. a CIO or some other manager, has distilled costs and benefits as depicted in Figure 10. In the model, nodes represent entities such as organizations or organizational units within a company. While the upper number within each node denotes each agent's index, the lower number shows the difference between each agent's standardization costs and standalone utilities. Both attributes are node-specific and can hence be netted. In contrast, information costs accrue between agents: they may be saved by standardization across the link between node i and j. Within this frame, a central observer can compute whether it is beneficial to standardize or not, which does not necessarily imply that all agents enjoy positive returns from the standardization, as illustrated by node 4. By using a common communication standard, node 2 and node 3 will save large information costs (Buxmann et al. 2011:42).

While a vivid discourse on extending central standardization models exists, e.g. by linking it with work on converter technologies (Wüstner 2005) or service-oriented architectures (Widjaja 2011), I believe it is more fruitful to consider decentralized models as in distributed infrastructures central control has only limited substance. In the words of Weitzel et al. (2006:494), optimal solutions "often fall short as decentralized agents' incentives differ from what a central planner's aggregate objective function may suggest". I turn to a model by Weitzel et al. (2006) as a reference point.

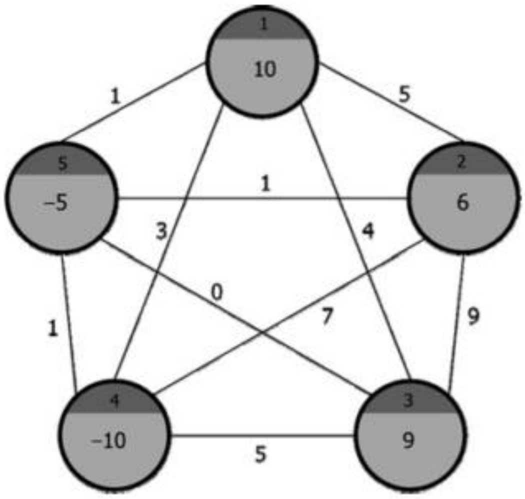

Figure 10. Example for standardization problem. Source: Buxmann et al. (2011:41)

A Unified Model of Standard Diffusion (Weitzel et al. 2006)

Weitzel et al. (2006) view standardization as a problem on a directed graph $N(g)$. E_i denotes the ex-post standardization utility for agent i modeled as the excess of direct network effects c_{ij} with partner j over standardization costs K_i. Agent i standardizes if the ex-post standardization utility $E_i > 0$. Equation 2.5 captures the agent i's utility function:

$$E_i = \sum_{j \text{ in } N(g)} c_{ij} x_j - K_i \quad with \quad c_{ij} > 0,\ x \in \{0,1\} \tag{2.5}$$

Where c_{ij} is the (network) utility of agent i from standardizing with agent j realized if and only if j also standardizes (indicated by the binary variable x_j) decreased by agent i's standardization costs K_i. The benefit c_{ij} is summed over all of i's peers $j_1,..,j_n$. Standardization costs K_i will be attributed to nodes while standardization utilities will be assigned to interactions between nodes i and j as a weight of the link ij.

Figure 11 shows a simple two-agent example (Weitzel et al. 2006:494). One may think of two firms, one of which (firm 1) considers joining the EDI network of the other firm (firm 2). If the small firm (firm 1) decides in favor of the implementation, it has to bear standardization costs of K_1=10 units. As the former firm is smaller, the utility it derives from the standardization will be small (9 units), compared to the larger gains of the second firm (30 units). At aggregate, standardization costs of 30 compare to utilities of 39, making bilateral standardization beneficial. From the (decentralized) perspective, however, firm 1 would not standardize since the costs (K_1=10) exceed the standardization gains (c_{12}=9). Because in this case it has complete information, firm 2 would also not standardize (Weitzel et al. 2006:494f.).

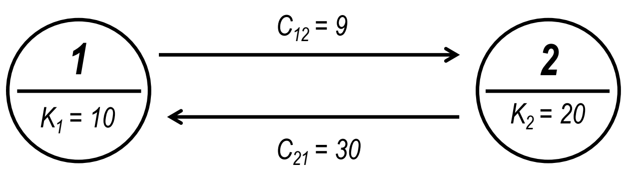

Figure 11. Two agent standardization example. Source: Weitzel et al. (2006: 494).

In the model, agents have no further information on its partners reasoning. Thus, they build expectations on the other agents' possible decisions. Each agent determines an expected value *Expected* $[E_i]$. The agent now standardizes if *Expected* $[E_i] > 0$. It incorporates each partner's standardization costs K_j, the number of partners φ_j, and standardization utility with partners c_{ji} in a probability p_{ij} replacing the binary variable x_j. Equation 2.6 gives the expanded calculus:

$$Expected[E_i] = \sum\nolimits_{j\ in\ N(g)} p_{ij} \cdot c_{ij} - K_i \quad with\ p_{ij} = \left(\frac{c_{ji} \cdot \varphi_j - K_j}{c_{ji} \cdot \varphi_j}\right) \tag{2.6}$$

$$s.t. \quad c_{ij}, c_{ji} > 0$$

That is, agents standardize if the utility from the standardization outweighs the costs.

Thus far, the model assumed binary (yes or no) decisions to standardize. In an extended model, agents select one out of q technologies with the highest (real) value. In general, q can represent any discrete number of technologies. To model multi-standard problems, the agents' decision function from Equation 2.7 is then adapted such that

$$Expected[E_{iq}] = \sum\nolimits_{j\ in\ N(g)} \left(\frac{c_{ji} \cdot \varphi_j - K_{jq}}{c_{ji} \cdot \varphi_j}\right) \cdot c_{ij} - K_{iq} \tag{2.7}$$

where q denotes the technology and K_{iq} the standardization costs for agent i. K_{jq} is the standardization costs for agent j for technology q. Since standardization costs vary across technologies, one can think of these standardization costs as different efforts to get rid of legacy applications, data and practices when implementing the new standard (Weitzel et al. 2006).

In simulations, standardization costs K_i are distributed to nodes randomly at normally (i.e. by a mean and a standard deviation). The standardization utility c_{ij} is distributed randomly at normal to links. As a result of the initial standardization, agents decide in favor of one technology. Agents may switch in a multi-standard situation as agents gain confidence in their neighbors' actual choices (Weitzel et al. 2006: 495).

The model illustrates that increases in the ratio of standardization costs versus benefits may cause a standardization gap in which agents will not standardize despite global efficiency of standardization (Weitzel et al. 2006:500). Furthermore, excess inertia can arise where agents will wait for their partners to standardize and as a consequence nobody standardizes. Furthermore, the authors begin to illuminate the impact of different network topologies on standardization patterns. They show that in close topologies – in which links between agents are drawn according to probabilities as a function of their proximity on a grid structure – domino effects will not occur as some components of the network are unconnected.

A Model of Direct and Indirect Network Effects (Beck et al. 2008)

Similarly, a study by Beck et al. (2008) examines how individuals adopt mobile communication standards as a function of network size-dependent indirect network effects and direct network effects contingent on an agent's position in the network. The study assumes simultaneous expectation building by all agents and considers several network structures.

2.5.6 Models on the Diffusion of Innovations

I turn to a set of models on the diffusion of innovations related to Roger's (2003) diffusion theory.

The Bass Model

An early account – that is still a good starting point – is the Bass model (Bass 1969). Although the model does not capture interactions among individual agents directly, the model incorporates some aspects of social influence. The model is built on two key parameters: a rate of spontaneous innovation and another rate at which the agents imitate other agents or adopt because others do so (Jackson 2008b:187). One may also interpret the former as a rate at which external shocks or triggering events occur and the latter as a sort of influence-based contagion or peer effect (Jackson 2008b:187). I refer to a dynamic process with discrete time intervals t (cf. Equation 2.1). Let *F(t)* be the fraction of agents having adopted the innovation by time *t*. The Bass model can then be described by the following difference equation

$$F(t) = F(t-1) + p\ (1\text{-}\ (F(t-1)) + q\ (1 - F(t-1))\ F(t-1) \tag{2.8}$$

where p is the rate of innovation and q is the rate of imitation (Jackson 2008b:187). The expression $p\ (1\text{-}\ (F(t-1))$ is the rate of innovation times the fraction of agents that have not yet adopted. The expression $q\ (1 - F(t-1))\ F(t-1)$ captures the mimicry process, where the rate of imitation is multiplied with two factors. The first factor, $(1 - F(t-1))$, is again the fraction of agents that have not yet adopted, and the second factor, $F(t-1)$, is the fraction of agents that have already adopted and can therefore be imitated.

The Bass model can be made to fit a variety of diffusion curves such as the typical S-shaped curve in Roger's (2003) theory on the diffusion of innovations by varying the parameters p and q. According to Jackson (2008b:187), the *ratio* of q and p is critical in determining the overall shape of the diffusion curve: initially, there are no agents to be imitated, F(t) is close to zero, and hence the equation can be approximated by p (Jackson (2008b:188). As time progresses, more agents can be imitated, which leads to the increase in the diffusion curve that can be interpreted as a self-reinforcing process. A balancing process occurs as time progresses, since there are more agents around that can be imitated but fewer agents to do the imitation (Jackson 2008b:188). Hence, the diffusion process saturates as there are no longer agents around that can imitate (Jackson 2008b:188).

Agent-based Models on Innovation Diffusion: Focus on Threshold Models

Recent work in a tradition of agent-based models has suggested going beyond variables on the systemic level and considering instead individual level interactions among heterogeneous agents to explain diffusion outcomes (Kiesling et al. 2011). In their review, Kiesling et al. (2011) identify three approaches: (1.) threshold models, (2.) utilitarian models, and (3.) state-transition models. Threshold models (1.) mostly assume that agents adopt if a certain proportion of an agent’s link partners have adopted (Valente 1996). The threshold is typically varied across the population and is either deterministic – agents decide to adopt deterministically once the threshold is reached – or probabilistic – i.e. agents adopt with a certain probability once a threshold is exceeded (Kiesling et al. 2011:193).

An example in the former tradition of deterministic thresholds is Valente and Davis (1999). The model brings in the social network structure and outlines a method to accelerate the diffusion of innovations using opinion leaders – being announced by members of the community as important by a questionnaire. Their claim on the effectiveness of opinion leaders is substantiated by utilizing a computer simulation that depicts the percentage of adopters as a function of time for varying initial adopters. The model assumes that each agent in the network ($N = 100$) has a social neighborhood and adopts if a certain fraction of its peers (15 percent) adopts. Based on whether the first 10 adopters were opinion leaders, randomly picked, or marginal – those being least nominated – diffusion curves and outcomes varied; the opinion leader strategy outperforms the other strategies. An example that draws on probabilistic thresholds is Bohlmann et al. (2010).

Utilitarian approaches (2.) mostly draw on a tradition of network effects as discussed in the previous chapter. Therefore, I do not discuss them in this section. State-transition models (3.) mostly draw on a tradition of infectious disease models such as the SIR (susceptible, infected, and resistant) or SIS (susceptible, infected, and again susceptible) models (Kiesling et al. 2011:194). These models build on probabilistic transitions between two states to explain adoption behavior. As existing models are highly stylized (Jackson 2008b), I do not include them for further consideration.

2.6 Comparison of Formal Models

I have introduced several models of path dependence and standard diffusion. This enables me to compare these models along several dimensions and to draw important conclusions. Within the discussion, I particularly focus on the extent to which existing models incorporate different aspects of the network structure in explaining diffusion outcomes.

First, self-reinforcing processes are fundamental for path dependence. I believe, in IT infrastructural contexts, it is vital to discern two network-dependent effects as shown in Table 9[9]: network-size effects (in short, network effects) and spillover effects. I showed that the traditional approach to standard diffusion has been network effect models assuming increasing utilities for agents with increasing adoption rates of a technology in a network. The benefit of adoption for an individual agent increases as a function of the network size, which is also the backdrop of seminal path dependence models (Arthur 1989; Leydesdorff 2000). Recent research has argued that the assumption that the network size N – the number of existing standard adopters – is all that matters for standard diffusion, is too restrictive (cf. Weitzel et al. 2006; Afuah 2013). This work particularly argued for considering individual agent interactions in explaining standardization outcomes. I have introduced work on the diffusion on innovation that showed convincingly how spillover effects shape the diffusion trajectory of a technology. Traditional path dependence models have not taken individual level contagion processes into account. In a fully-meshed network, network effects and spillover effects cannot be distinguished[10] as both fall together and it remains

[9] My research suggests that one should also account for adaptation (or learning) effects that work on an individual node or agent level but as my main focus is different forms of interactions across nodes or agents, I exclude these processes from further consideration.

[10] A similar problem to discern average-group influences and peer effects has long been central to sociology; both cannot be distinguished when an agent is linked to all other agents in a network,

unclear whether influences spill over from direct interaction partners or whether they are a consequence of the standards spread in the network.

Table 9. *Self-reinforcing mechanisms in IS standard diffusion research*

↓	Definition	Mechanisms	Theoretical antecendants
Network effects	Incentive to adopt a standard (or take any action) increases as a function of the network size	Credibility of standard; installed base advantages; availability of complementary services and products	Arthur (1988); Arthur (1989); Hanseth (2000); Katz and Shapiro (1985); Liebowitz and Margolis (2013)
Spillover effects	Incentive to adopt a standard (or take any action) increases as a function of the extent to which others do so	Conformism; peer pressure, coercision and mimesis; learning from the experiences of others	Aral et al. (2009); Jackson (2008a); Arthur and Lane (1993); Narduzzo and Warglien (1996)

A second relevant dimension is the *network topology* – the structure of linkages defining the underlying network. Traditional models of path dependence, such as Arthur's (1989) model and important extensions (Leydesdorff 2000), can be re-casted as a fully-meshed network in which all agents are linked (Draisbach et al. 2013). This form of interaction is very particular and does not capture many real world interactions. I have presented several models utilizing other, non-complete network topologies. In addition to random networks, which have often been used as a constructive baseline (i.e. in Weitzel et al. 2006; Beck et al. 2008; Draisbach et al. 2013), presented models often extend their approach to one or two other network topologies. Draisbach et al. (2012, 2013) draw on formation algorithms for two social network topologies. Weitzel et al. (2006) discuss implications from a simple, grid distance-based – network topology. Valente and Davis (1999) utilize an empirical social network. While many important network topologies have been discussed, I see a particular need for research on mixed forms between preferential attachment and random networks (hybrid models) as they enable better fitting to important real world network's characteristics, such as degree distributions, clustering coefficients, and average path lengths (Jackson 2008b).

which is known as the "reflection problem" in seminal studies on social interactions from sociology (Manski 1993). For concreteness, think of a class of students in which each student is influenced by every other student in the class (e.g. in his or her decision which movie to watch). In such situation it may not be possible for an observer to distinguish whether the average taste of all students may have influenced the student or whether this was due to specific influences from particular students within the class. In fact, both forms of interaction fall together. In a situation in which the students is, however, both influenced by average characteristics of the class as well as by particular peers in his reference group, observing the outcome of the experiment will enable the observer to discriminate between both types of influence.

A third important dimension is the *approach to individual agent decision-making*. The models differ in their approach to individual agent decision-making. One approach – that has been commonly used in standard diffusion models which come from a tradition of centralized optimization (e.g. Weitzel et al. 2006; Beck et al. 2008) – is that all agents in the network decide or build expectations simultaneously; then, the simulation round is closed, all decisions are collected and implemented. A second approach – commonly used in models of path dependence – is that agents decide sequentially (Arthur 1989; Draisbach et al. 2013; Leydesdorff 2000); one agent enters the network, decides, and then again the next agent enters. Based thereupon, sequential decision-making could happen randomly or be dependent on the positioning of the trigger node in the network. I conclude that none of the presented approaches consider the actual trajectory of the 'domino effect' through the network. I believe that there is a need for research on the effect of the position in which a triggering shock penetrates the network on the diffusion outcome.

Growth is another important dimension. In static networks, nodes are created at the initialization and wired according to certain probabilistic rules (Jackson 2008b). Most of the presented models fall into this category (Beck et al. 2008; Draisbach et al. 2013; Valente and Davis 1999; Weitzel et al. 2006). One can conceptualize urn-type models, such as the model by Arthur (1989) and Leydesdorff (2000) as a growing network in which agents form links to all other agents in the network. Urn-type models, however, assume that the number of formed links grows as a function of the network size. This approach is very limited. Existing models have not yet explored the impact of different growth logics – how agents that enter a network form links to other agents – on diffusion outcomes.

Finally, models also account differently for *individual agent heterogeneity*. One approach – found only in a limited number of early models on the diffusion of innovation (e.g. Valente and Davis 1999) – is to assume identical thresholds (or preferences) for all agents in the network. To maintain analytical traceability, early path dependence models have restricted themselves to few, heterogeneous groups of agents (Arthur 1989; Leydesdorff 2000). Recent models from standard diffusion have moved towards heterogeneous agents, where attributes such as standardization costs are distributed uniformly at random across agents (Beck et al. 2008; Weitzel et al. 2006). Previous models have, however, utilized one-dimensional representations of agent attributes. I see a need for research on how agent attributes interact in shaping diffusion outcomes. Table 10 summarizes the comparison of the models along the discussed dimensions.

Table 10. Comparison of selected path dependence and standard diffusion models

		Network topology	Individual agent decision making	Heterogeneous agents	Network influence processes		Growth	Path breaking interventions
					Network effects	Spillover effects		
Innovation diffusion	Bass 1969	no	n/a	n/a	yes	no	no	no
	Valente 1999	specific	simultaneous	no	no	yes	no	opinion leaders
Path dependence	Arthur 1989	fully-meshed	sequential, random	one-dimensional	yes	no	simple	no
	Leydesdorff 2000	fully-meshed	sequential, random	one-dimensional	yes	no	simple	no
	Draisbach et al. 2013	specific	sequential, random	one-dimensional	no	yes	no	no
Standard diffusion	Weitzel et al. 2006	specific	simultaneous	yes	yes	no	no	no
	Beck et al. 2008	specific	simultaneous	yes	yes	no	no	no

Chapter 3

Research Gap

This chapter motives my research that aims at improving existing models in information systems research to better understand problems of IT infrastructure path dependence.

3.1 Motivation for an Alternative Modeling

Previous models of path dependence and standard diffusion enable a general understanding of path building processes in airline distribution IT and organizational IT infrastructures through the notion of network effects. However, I gained the impression that the limitations of existing models call for a recasting. Expert interviews (refer esp. to oS10 and oS11) confirmed my impression that traditional path dependence models, i.e. Arthur 1989, characterize outcomes from diffusion processes too starkly. Traditional models of path dependence overestimate the susceptibility of a network to lock-ins as network influences remain undifferentiated across different agents. These models tend to a broad "winner-take-all" view while leaving the question unanswered of how paths build up in segments, groups, or clusters. I contend that an alternative modeling must account for individual level interaction patterns and different growth logics.

Consider the example of organizational IT infrastructures. Consistent with Aier et al. (2009) and Matthes (2008), my research suggests that organizational IT infrastructures, for mid-sized companies, consist of several hundreds or even thousands of information systems, cobbled together in nontrivial ways. Organizational IT infrastructures evolve over extended time periods and new systems and extensions – vital to fulfill changing business requirements – are constantly added by central IT departments and business units. Standards spill over from one system to another as they enable compatibility across departments, actors, and systems. Complexity builds up over time and standards increasingly diffuse. Fundamental changes move out of reach. For such systems, assuming a static interaction structure among agents is too restrictive.

In addition, also organizational IT infrastructures in airline distribution illustrate my main argument that interaction patterns and growth matter. Recall that, in discussing problem areas with respect to booking classes, I illustrated how the booking class standard increasingly diffused in airline activities over time: revenue management, customer loyalty, codesharing, and corporate customer contracts are only a selection of the aforementioned areas drawing on a large number of IT systems. These systems evolved over decades and interviews provide evidence for legacy in airlines' IT infrastructures tracing back until the 1960's.

Turning to the interorganizational level, recall that booking classes connect several hundred or thousand airlines having various codeshares and other alliance relationships. The significance of alliances follows an increasing trend. The three foremost alliances combined – Star Alliance, Sky Team, and Oneworld – flew nearly 73% of all passengers worldwide by March 2009 (Hu et al. 2013). The aggregate number of members grew from 33 in 2003 to

52 in 2010 (Hu et al. 2013). Since its foundation in 1997, Star Alliance members entered and dropped out with a yearly rate of 15.9%, exemplifying alliance agglomeration.

3.2 Research Questions

3.2.1 Path Building

I suggest as a first research question:

Research question 1: *How does a network's growth logic affect path building?*

Beyond its direct implications for research on IT infrastructures, this question is important, because growth processes are essential in many organizational settings. On a market level, organizations that enter a field can be portrayed as nodes forming links to other nodes. Alliances, consortia, or joint ventures compete for resources, power, status and influence (Burger and Sydow 2014; Provan et al. 2007; Sydow 2010). The moment when an organization enters a field or group is often a moment of technological choice. Pressure to conform can force the organization to the 'de-facto' standard solution in the alliance reinforcing the overall diffusion of technology in the group. A variety of outcomes from diffusion processes such as islands of shared technologies or local clustering makes me believe that the conceptual underpinning of path dependence theory – urn-type models focusing on the network size – is too restrictive. Urn-type models assume fully-meshed networks. New agents link to all other agents in the network. As a consequence, they mischaracterize important features of growth processes such as the degree of interaction or preferentiality. Paul David, a pioneer in research on path dependence, for instance, outlines a path-dependent process in which complementary elements in a growing system tend to cluster together more and more closely over time, which creates misfit costs for ill-fitting new elements (David 1994). However, conceptualizing such process is beyond the power of urn-type models.

Network formation – a subfield of network analysis – provides models of growing networks explaining how nodes entering a network select who to interact with (Jackson and Zenou 2013; Jackson 2008b). Network formation models have a greater power than traditional urn-type models as they can incorporate selective influences and discern different types of network influences, which is not possible with fully-meshed urn-type models. Newly implemented systems or extensions to existing systems may be understood as nodes entering a network that form links to other nodes. These links may be formed uniformly at random but often times they will form preferential - proportional to the importance or centrality of existing systems – or in other, more complex ways. The main proposition that I want to examine is how a network's growth logic affects the number of available options (e.g. standards, action patterns) in the system.

3.2.2 Path Breaking

The example of global airline distribution IT points to the interesting question of how existing paths can be extended, complemented (or even replaced in the long-term) by creating a new path utilizing more effective standards. I thus suggest a second set of research questions:

Research question 2: *(a) How will interaction patterns affect whether a new standard will diffuse to a nontrivial fraction of agents?*

(b) Which agents should be targeted by network interventions to facilitate a new standard's diffusion?

This first part of this question (2a) is of obvious importance. Beyond the direct application to airline distribution standards, it is closely related to other standardization problems such as EDI/XML adoption in retailing (Lyytinen and Damsgaard 2001; Wareham et al. 2002) or the adoption of data standards in the financial service industry. Furthermore, it is clear that the topology of linkages can be very important in determining the outcome. I assume that networks with disconnected, closed topologies will exhibit different diffusion patterns than, for example, fully-meshed networks (Weitzel et al. 2006). Moreover, networks with "power law" structures – that feature several important hubs – might foster different diffusion patterns than networks in which organizations have roughly the same degree (Elliott et al. 2014).

The second part of this question (2b) focuses on targeted intervention strategies. Triggering events, may it be random or targeted interventions, play an important role in any path constitution process (Sydow et al. 2012). While most research on path breaking has so far been devoted to clarify conceptual issues, a recent stream of research also began to explore systematically the effectiveness of different path breaking strategies (Vergne and Durand 2010). Going beyond the question of whether paths can be broken to how this can be done most effectively is important as the economic use of resources is vital in any organizational context. Often, it may be useful to focus on selected "key players" that drive the overall diffusion of a standard most effectively (Ballester et al. 2006; Borgatti 2006). Most favorably, identifying such "driver nodes" could allow for full control over diffusion outcomes (Liu et al. 2011b). The question is of further theoretical importance as it contributes to a recent and fruitful stream of research on targeted network interventions (Valente 2012).

Part II

Path Building

Chapter 4

Standard Diffusion in Growing Networks

4.1 Modeling Preliminaries

I suggest a model of standard diffusion in a network of N nodes linked through different forms of interactions[11]. I envision two examples to operationalize the model. Firstly, think of an organizational IT architecture where business units raise demands for IT support. In the model, nodes operationalize in new systems or extensions of existing systems building upon and linking to particular existing systems. Interactions materialize in specific technical interfaces. Secondly, think of a network of airlines having codesharing agreements. Nodes operationalize in particular airline organizations and links represent ties of interorganizational collaboration such as codeshare agreements. Codeshare agreements, for instance, affect technology choice, as flight availabilities must be exchanged between partners based on common distribution standards (Hu et al. 2013). In the model, I assume positive network influences: the presence of interactions increase an actor's incentive to select the technology used by its partners. This is plausible for organizational IT infrastructures as well as platforms for airline cooperation.

Networks can be classified as *static* or *growing* (Jackson 2008b). Studying standard diffusion in the former will serve as useful when the network is in stasis and does not show many fluctuations. All agents are created at the same time and then "links are drawn between them according to some probabilistic rule" (Jackson 2008b:78). Most predecessors in standard diffusion subscribed to this approach (Buxmann et al. 1999; Draisbach et al. 2013; Weitzel et al. 2000, 2006). I, however, find a second class of models – in which new agents enter the network over time and attach to others – more useful as I am interested in how growth affects path building.

My starting point is a hybrid random growth model (Jackson and Rogers 2007) in which new agents form links by attaching to a certain fraction of agents uniformly at random and to another fraction as "friends-of-friends", chasing adjacent links from their random encounters. Hybrid growth models set themselves apart from other random growth models by their ability to match realistic network structures of growing random, preferential attachment and mixed networks regarding clustering coefficients, average path lengths, and degree distributions (Jackson 2008b). Few models have combined non-random, growing networks with strategic agents that select technologies based on a cost-benefit analysis (Jackson 2008b).

4.2 Operationalization of the Network Growth Model

In the following, I introduce the main ingredients of the model: (1.) network initialization, (2.) network formation, and (3.) strategic agents.

---

[11] Refer to Fuerstenau and Kliewer (2014) for an earlier version of the model published at ECIS conference

4.2.1 Network Initialization

As a starting point, I suggest creating an initial (static) network *N(g)* that consists of a fixed set of n nodes and links between those nodes. These links can be described by a real-valued $n \ x \ n$ (adjacency) matrix g, where g_{ij} represents the (possibly directed and weighted) relation between node i and j (cf. Jackson 2008b:21). Links denote interactions exhibiting a positive externality to adopt the technology used by an agent. I will restrict the analysis to undirected networks in which $g_{ij} = g_{ji}$ for all nodes i and j. It will be standard that the values in g will be restricted to 0 and 1; hence, the network is unweighted. As shown in Figure 12, the network is initialized using different standard network types described in the following.

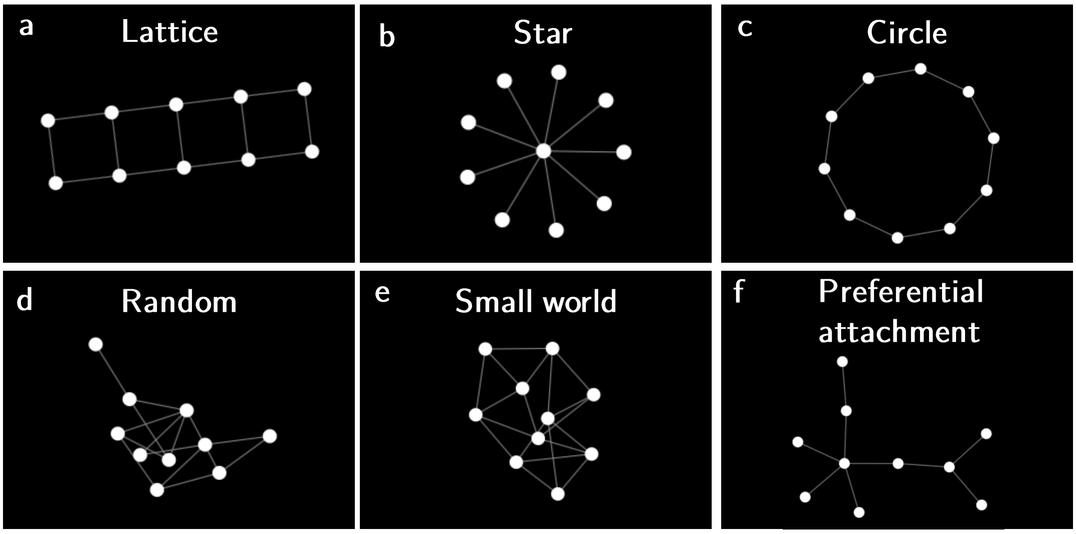

Figure 12. *Different types of initial networks with nodes (circles) and links (lines)*

Static Random Networks

As the most basic network type, I refer to *Poisson random networks* (cf. Jackson 2008b:9-14). In random networks (cf. Figure 12d), each link is formed with a given probability λ, and the formation is independent across links (cf. Jackson 2008b:9). This serves as a useful base case when no other theory or observations exist (cf. Jackson 2008b:77).

Preferential Attachment Networks

As another useful network type, I refer to preferential attachment networks (cf. Jackson 2008b:130-134). Preferential attachment models (cf. Figure 12f) will be supportive as a convincing logic explicates why such networks form: new nodes in a growing network attach preferentially to nodes which already show more importance. This is reflected in the model of Barabasi and Albert (1999) by the fact that new nodes attach to nodes with a probability proportional to their degree. Consequently, the distribution of degrees shows “fat tails” – which means that there are more nodes with a very high degree than usually expected from a random growth process. The distribution of degrees exhibits another interesting feature: more nodes with lower degrees will be observed as many nodes will not receive as much attention as under random growth (Jackson 2008b:131). Consistent with Barabasi and Albert (1999), I expect that preferential attachment is, especially in technological contexts, fairly common.

Centralized vs. Decentralized: Star, Lattice, Circle, and Small World Networks

Further network types can be grouped according to their degree of centralization (Borgatti et al. 2009:893). Star networks (cf. Figure 12b), for instance, are strongly centralized as they join together all power or influence to a single player. This player channels all communication in the network. Imagine a star network with a large "core" organization surrounded by many smaller "peripheral" organizations, each of which is linked to the core organization. This could for instance emulate a network of airlines attached to a single GDS platform. Lattice (cf. Figure 12a) or circle networks (cf. Figure 12c) are, in contrast, more decentralized as each node depends only on m direct neighbors. A mixed form is small world networks (cf. Figure 12e) in which a circle is rewired, which results in smaller average path lengths and diameters (cf. Watts and Strogatz 1998).

Technology Diffusion in Initial Network

I am interested in how growth affects path building. Consequently, the way in which technologies diffuse in the initial network is not central for my approach. However, initial conditions will often predetermine path building processes before further growth sets in (cf. Sydow et al. 2009). Think of a biased process as a result of a *network imprint* (Johnson 2007; Marquis 2003; Schreyögg and Sydow 2011), or *shadow of the past* (Sydow et al. 2009). Moreover, the mechanics of many network formation algorithms such as preferential attachment require a network to already exist before further growth can set in.

Consequently, we have to consider that the initialization procedure can create an initial upfront bias towards one technology which would predetermine the subsequent path building process (Page 2006). Beyond the obvious random initialization with a given probability λ and random assignments of technologies, I thus suggest two simple ways to assign technologies in the initial network. Firstly, a *minimal set strategy* and secondly a strategy to *diffuse technologies from hubs*. Regarding the former, I create a minimal set of nodes equal to the number of technologies (k) but also not larger than that. Assume, for instance, we consider two technologies competing for adoption. One may start with the smallest possible network of two nodes and assigns one technology to each of the nodes at random. This avoids any upfront bias towards any technology that could influence the trajectory of the subsequent path building process.

Algorithm A.1 shows how to initialize a minimal, unbiased set of agents. Lines 1-3 set up k nodes and k technologies. Lines 4-8 assign exactly one exclusive technology to each node.

Algorithm A.1 Initialize a minimal set of nodes

```
    k := user-input where k is the number of technologies
1:  to setup
2:    lst-technologies := create list of length k from sufficiently large list of all technologies
3:    create k nodes
4:    i := 0
5:    while i < length lst-technologies do
6:      foreach item i sort nodes do st-tech := item i lst-technologies end foreach
7:    end while
8:  end setup
```

There are, however, drawbacks from initializing minimal sets. First and foremost, as described by Arthur (1989), early events will rapidly predetermine the process and one may hence see only little influence from the pre-existing "installed base". In contrast, standardization seldom starts from scratch (Hanseth 2000); standards will often already exist when further growth sets in. Another way to initialize the network is thus to simulate the previous diffusion process based on assumptions on the pre-standardization history.

Observed tendencies towards clustering around important hubs in the empirical examples suggest another strategy. I find it superior to create an initial preferential attachment network, assign different technologies uniformly at random to hubs and then to simulate a contagious process triggered from the hubs. Thus, I introduce Algorithm A.2. The algorithm firstly creates a preferential attachment network of n nodes. Then, a fraction of all nodes with above-average degrees – the hubs – are selected and technologies are assigned uniformly at random to these hubs (lines 3-6). Then, the algorithm treats these predetermined nodes as trigger nodes and triggers a cascade running through the entire network. Each of the trigger nodes' neighbors is stored in a list (lines 8-10) and then these nodes assess which technology they should adopt by computing for each technology the number of adopters in its neighborhood (lines 11-17). Then, this particular node adopts one of the technologies with the maximum number of adopters in its neighborhood. The cascade assesses recursively whether there are any nodes left which have not yet been assessed and potentially adds them to the list of nodes that still need to be checked (from line 18). This process continues until the entire reachable network is assessed. Finally, the algorithm converges. As the outcome of the algorithm, any node within the components in which a trigger node resisted has been assigned to exactly one technology.

Algorithm A.2 Diffusion of technologies from triggering hubs

```
1:  compute average-degree in the network
2:  st-tech := empty for all nodes
3:  foreach node with count link-neighbors > average-degree do
4:    st-tech := one-of lst-technologies,
5:    reached? := true
6:  end foreach
7:  lst-radius1 := all nodes with st-tech = one-of lst-technologies
8:  foreach item lst-radius1 do
9:    perform a radial search that adds all neighbors in radius 1 to lst-radius1
10: end foreach
11: i := 0
12: while i < length lst-radius1 do
13:   foreach item i do
14:         check which technology to adopt by assessing the agent's payoff function
15:         reached? := true
16:   end foreach
17: end while
18: if any node with not reached? then
19:       perform a radial search that adds all neighbors in radius 1 to lst-radius1
20: else converge by checking for each node in the lst-radius1 which technology to adopt
21: end if
```

4.2.2 Network Formation

My theoretical foundation to operationalize a growing network is a hybrid random growth model as described by Jackson and Rogers (2007). I construct a simple and yet powerful growth process: each period one agent i_1, i_2,.., i_t enters a network and links to m agents. Let m designate the *degree of interaction* where $m \in \mathbb{N}^+$. Let α designate the *degree of preferentiality* ($\alpha \in \mathbb{R} \mid 0 \le \alpha \le 1$).

What is the rationale for different *degrees of interaction (m)*? Technology adoption will certainly depend on whether an agent is influenced by a few close peers or by a broader community of distant others. Heavy interactions with many distant others are usefully distinguished from low levels of interaction where few peers influence an agent's decision (cf. Borgatti et al 2009).

The next step will operationalize with whom to interact. The simplest way to do so is the extent to which links form uniformly at random or preferentially. Drawing on Jackson and Rogers (2007), new agents in this hybrid model form $\alpha \cdot m$ links uniformly at random[12] and $(1 - \alpha)\cdot m$ links by searching locally through the structure of the network (e.g. meeting friends of friends). Consequently, m splits into random meetings (m_r) and network-based encounters (m_n). Figure 13 depicts the idea: Figure 13a shows the elements being picked uniformly at random while Figure 13b shows elements being picked as friends-of-friends. If α equals one, agents attach completely at random whereas if α is closer to zero, agents attach more preferentially. If α equals zero, I operationalize the model by a usual preferential attachment algorithm in which agents form links to other nodes with probabilities proportional to their degree (Barabasi and Albert 1999).

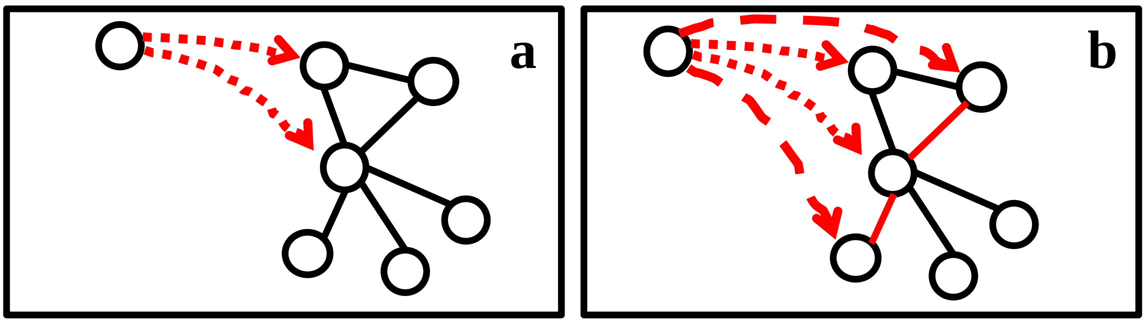

Figure 13. *Hybdrid random growth. Source: adapted from Jackson and Rogers (2007)*

Algorithm A.3 describes the hybrid random growth process. I assume that the network is non-empty such that $n > 0$ nodes already exist and at least one link between these n nodes is present. Let *lst-parents* and *lst-fof* denote the randomly selected nodes and the nodes picked as friends-of-friends, respectively. Then, lines 10-20 determine the fraction of random and friends-of-friends-based encounters, lines 22-27 pick parent nodes at random, lines 29-41 pick friends-of-friends, and lines 43-44 create links to both types of nodes.

[12] If $\alpha \cdot m + (1 - \alpha)\cdot m > m$, then the number of network-based encounters is adjusted downwards. Imagine, for instance, $m = 5$ and $\alpha = 0.5$. Then, round($\alpha\cdot m$) + round $((1\text{-}\alpha) \cdot m) = 6 \neq m$. Thus, m_n is set to $m - mr$.

Algorithm A.3 Hybrid random growth

```
m := user input, alpha := user input, time-limit := user input
to go
  if ticks = time-limit then stop end if
  create-nodes 1 [ grow-hybrid m ]
  ticks := ticks + 1
end go
to grow-hybrid [ m ]
  node_i := self
  others-set := [ ], lst-parents := [ ], lst-potential-fof := [ ], lst-fof := [ ]
  if m > count other nodes then m := count other nodes end if
  let mr := alpha * m                                   > number random encounters
  let mn := (1 – alpha) * m                             > number friends-of-friends
  if round mr = 0 then preferential-attachment1)
  else
        mr := round mr                                  > mr becomes an integer
        mn := m - mr                                    > mn is set to remaining nodes
        foreach other node do others-set := lput self others-set end foreach
  end if
  i := 0, node_j := null
  if mr > 0 then
    while i < length others-set and i < mr do           > pick parents at random
      node_j := one-of others-set
      lst-parents := lput node_j lst-parents
      others-set := remove-item node_j
    end while
  end if
  foreach lst-parents do                                > pick friends-of-friends
    foreach link-neighbors do
        lst-potential-fof := lput self lst-potential-fof
    end foreach
  end foreach
  lst-potential-fof := remove-duplicates lst-potential-fof
  lst-potential-fof := remove-item node_i
  h := 0
  while h < mn and h < length lst-potential-fof and length lst-potential-fof > 0 do
    foreach one-of lst-potential-fof do
      lst-fof := lput self lst-fof
      lst-potential-fof := remove-item self lst-potential-fof
    end foreach
  end while
  foreach lst-parents do create-link-with node_i end foreach
  foreach lst-fof do create-link-with node_i end foreach
end grow-hybrid
```

1) This part of the algorithm is not described here, see Barabasi and Albert (1999). In contrast to the hybrid growth algorithm, Barabasi and Albert's (1999) algorithm does not assume any random encounters but instead picks nodes with probabilities according to their degrees.

Why should we consider different *degrees of preferentiality*? Preferential attachment is firstly empirically justified. Many social and technological processes show degree distributions in which a few central players accumulate above-average numbers of links (Barabasi and Albert 1999; Jackson 2008b). The network literature discusses several reasons. Forming links to central players in contrast to non-central players often yields different benefits and costs. Benefits may arise from a central player's connectedness and their more robust or influential position (cf. Bothner et al. 2010). Central players may also have accumulated considerable resources and capabilities which increases their attractiveness (Valente 2012).

At this point, each new agent formed a fixed, absolute number of links ($m \in \mathbb{N}^+$). I next turn attention to cases in which the number of links that each new agent forms grows over time with the network size. Refer to chapter 2.2.2 for a discussion of network size-dependent effects. Network effects will, for instance, arise if agents observe the installed base of a technology in the market. Consequently, an agent's later entry results in more information being available as more agents already chose which technology to use. Drawing on a term introduced by Fichman (2004), let m_{rel} designate an agent's *susceptibility to network effects* where m_{rel} is the fraction of agents in the network at time t that a new agent forms links with ($m_{rel} \in \mathbb{R} \mid 0 \leq m_{rel} \leq 1$). Assuming m_{rel} is constant over time, the number of links grows proportionally to the network size in t. For concreteness, consider that m_{rel} equals 0.5. Then, in t_1, a new agent processes information from $0.5 \cdot n_0$ other agents, in t_2 from $0.5 \cdot (n_0 + 1)$, in t_3 from $0.5 \cdot (n_0 + 2)$ agents and so forth. If m_{rel} equals one, each new agent processes information on the state of any other agent. This describes an agent's calculus in which it assesses a distribution over outcomes, e.g. the technologies' shares in a market. Let p be a binary variable that designates whether growth is proportional ($p = 1$) or non-proportional ($p = 0$). I modify Algorithm A.3 to account for different growth logics as shown in Algorithm A.4.

Algorithm A.4 Proportional versus non-proportional growth

```
p := user-input, m := user-input, m_rel := user-input
to-report find-m
  if p = 1 then m := round count nodes · m_rel
  else m := m
  end if
  report m 1)
end find-m
```

1) The output of *find-m* is the input for the *grow-hybrid* function (refer to Algorithm A.3)

As shown in Table 11, three main factors describe the network's hybrid growth process.

Table 11. Parameters of the model that control a network's growth process

1. Proportionality (p)	Are links forming relative to the network size or not?
2a. Degree of interaction (m)	What number of links ($m \in \mathbb{N}^+$) form in absolute ways?
2b. Degree of susceptibility to network effects (m_{rel})	What is the fraction of links forming relative to the network size?
3. Degree of preferentiality (α)	To what extent is link formation random or preferential?

4.2.3 Strategic Agents

I turn to the question of how agents in the model decide which of several technologies to use. Consistent with Arthur (1989), Weitzel et al. (2006), and Beck et al. (2008), I assume that agents' decisions to adopt technologies are irreversible as they create large fixed costs and trigger extensive capability building, integration, and adaption processes. Agents in the model decide which technology to adopt based on (1.) a technology's standalone utility and (2.) network influences. Essentially, the distinction captures the trade-off between actors' individual preferences and the way the actor is influenced by the broader social, economic, institutional, or organizational environment (cf. Krackhardt 2001). One expert from airline pricing designated these network influences as "inherent necessities" that create pressure to conform (refer to expert statement in interview oS11).

I define that agent i of type ν selects one of k technologies with the highest payoff $U_{\nu k}$ according to Equation 4.1 such that

$$U_{\nu k} = \beta \cdot a_{\nu k} + (1 - \beta) \cdot [((1 - p) \cdot b_{\nu} \cdot \Sigma_{m \text{ in } N(g)} x_k) + (p \cdot b_{\nu} \cdot \Sigma_{mrel \text{ in } N(g)} x_k)] \quad (4.1)$$

where $a_{\nu\kappa}$ designates i's preferences towards technology k bringing in agent heterogeneity. Let $a_{\nu\kappa}$ be a positive, real-valued number ($a_{\nu\kappa} \in \mathbb{R} \mid a_{\nu\kappa} \geq 0 \; \forall \nu, \kappa$). Often, $a_{\nu\kappa}$ may be the result of joining a set of attributes (a vector of real or binary numbers) by an arbitrary mathematical function. For concreteness, think of two attributes, a real-valued variable *technology preference* and a binary variable *improvisational capability* (e.g., designated by (5 1)). The benefit of a new technology may then be unlocked only if the variable *improvisational capability* is non-zero; *technology preference* may thus be multiplied with the binary value, i.e. $a = a_1 * a_2 = 5 * 1 = 5$.

Let β designate the *network influence strength* designating the total importance of network influences in comparison with a technology's inherent qualities ($\beta \in \mathbb{R} \mid 0 \leq \beta \leq 1$). If $\beta = 1$, i's decision will fully depend on inherent qualities of the technologies. If, in contrast, $\beta = 0$, only network influences will influence i's choice. With respect to network influences, I distinguish two distinct types of network influences: the first is a network size-dependent effect (in short, *network effect*) arising from the average characteristics of a fraction of other agents in the network. The second type of network influence is a *spillover effect* arising from direct influences from an agent's peers. The expression $((1 - p) \cdot b_{\nu} \cdot \Sigma_{m \text{ in } N(g)} x_k)$ captures the spillover effect that adds up an integer number of peers (m). It remains a fixed, absolute value for each agent entering the network. Whether a peer has adopted technology k is defined by the binary variable x_k; it is one if the other agent has adopted, and zero otherwise. The expression $p \cdot b_{\nu} \cdot \Sigma_{mrel \text{ in } N(g)} x_k$ captures the network effect. To compute the network effects, I add over a fraction of agents in the network. Let m_{rel} be the number of sampled agents; the network effect grows proportional to the network size if the number of agents increases over time. Let p be a binary variable that enables switching between network effects, designated by the term $(1 - p) \cdot b_{\nu} \cdot \Sigma_{m \text{ in } N(g)} x_k$, and spillover effects, designated by the expression $p \cdot b_{\nu} \cdot \Sigma_{mrel \text{ in } N(g)} x_k$. Let b_{ν} be the *network multiplier* that captures the magnitude of network influences for each agent group ν. It is a non-negative, real-valued number.

Algorithm A.5 operationalizes my conception of how agents decide in the case of $k = 2$ technologies. In the algorithm, let *lst-technologies* designate the set $\{A, B\}$ of all technologies of length k. Let further *lst-*ν designate the set $\{R, S\}$ of all types of agents of length ν. Furthermore, let *lst-payoffs* designate each agent's real-valued payoff vector. Finally, let x_A and x_B be binary variables that indicate whether the agent adopts technology A or B, respectively. Then, lines 3-5 set the payoff vector to the number of each agent's link neighbors adopting technology A or B. Lines 7-14 compute each agent's utility by multiplying network influences with the network multiplier as well as adding the base utility, depending on the agent type. Lines 15-16 set the adopted technology to the one that maximizes the agent's payoff.

Algorithm A.5 Payoff computation for $k = 2$ technologies and $\nu = 2$ agent types

1: **for** agent i^* **do**
2: i := 0, lst-payoffs := k values [0]
3: **while** $i <$ length lst-technologies **do**
4: x_κ := count link neighbors with technology k
5: lst-payoffs := replace-item i lst-payoff x_k
6: **end while**
7: **if** ν_i = (item 0 lst-ν) **then** *// payoff function for R-agent*
8: lst-payoffs := replace-item 0 lst-payoff ((β * (b_1 * (item 0 lst-payoff) + (1-β)*a_{RA}))
9: lst-payoffs := replace-item 1 lst-payoff ((β * (b_1 * (item 1 lst-payoff) + (1-β)*a_{RB}))
10: **end if**
11: **if** ν_i = (item 1 lst-ν) **then** *// payoff function for S-agent*
12: lst-payoffs := replace-item 0 lst-payoff ((β * (b_2 * (item 0 lst-payoff) + (1-β)*a_{SA}))
13: lst-payoffs := replace-item 1 lst-payoff ((β * (b_2 * (item 1 lst-payoff) + (1-β)*a_{SB}))
14: **end if**
15[3]: **if** max(lst-payoffs) = item 0 lst-payoff **then** x_A := 1
16[3]: **if** max(lst-payoffs) = item 1 lst-payoff **then** x_B := 1

[3] when both technologies are the maximum one is chosen uniformly at random

Setting base preferences to zero and assuming non-proportional spillovers with four agents, Figure 14 shows a simple example where a new agent adopts technology A as a result of stronger influences from A-adopters despite equal diffusion rates of both technologies – A and B – in the network.

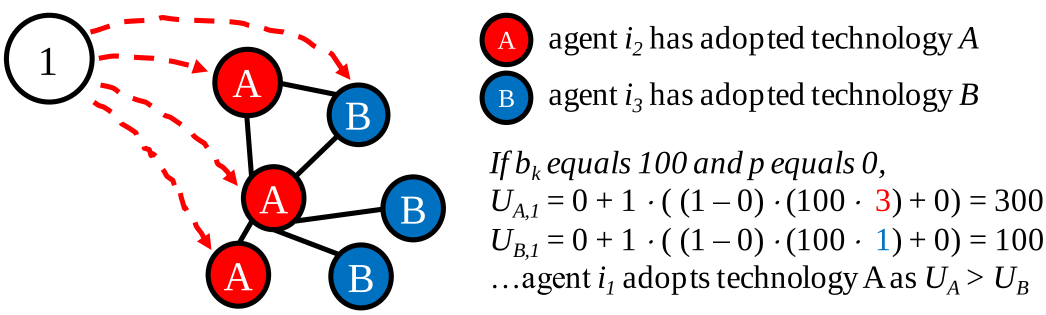

Figure 14. Simple illustration of decision calculus for a new agent

4.2.4 Measuring Diversity in Networks

I am interested in the extent to which (*i*) one standard comes to dominate or (*ii*) multiple standards persist in a network that describes an IT infrastructure. A straightforward way of measurement is the rate of adoption for each available technology (cf. Arthur 1989). In addition, I suggest using a *diversity index*, a *network-adjusted measure of homogeneity,* and *individual misfits* to quantify a network's state of heterogeneity. As I will show, these measures deliver complementary information contents.

The phenomenon of path dependence describes dynamic processes of diminishing scope of action; a state of lock-in is characterized as a situation in which only one solution or action pattern remains (Sydow et al. 2009). As the situation finally settles towards one solution – where multiple solutions have been possible ex-ante – path-dependent processes have been described as non-ergodic (Arthur 1989). According to a distinction by Page (2006), one can characterize models of path dependence as describing situations where a system moves from a stochastic state to a state of equilibrium. Nevertheless, path dependence theory suggests that a system will not tip from a situation of contingency (or more formally, a stochastic state) to a situation of lock-in (or more formally, equilibrium) by a single event. Rather one or several critical events may turn the system into one path and then small changes become accumulated as positive feedback narrows the scope until only one possible action pattern remains (cf. Sydow et al. 2009).

My model should hence enable us to quantify how diverse the (intermediate) states of a process are to evaluate whether the system drove into a state of lock-in. It should allow discerning networks in which the scope of action diminishes over time and networks in which a sudden tipping occurs. Furthermore, measures of lock-in should account for the network structure to distinguish whether local nodes group together – and adopt the same standard – or whether diffusion outcomes are diverse by mere accident.

Diversity Index

Diversity indices have long been used to quantify the variety of different types in sets of elements (cf. Page 2011). In history-dependent systems, diversity indices also help to quantify the likelihood of changes in outcomes (Lamberson and Page 2012). Consistent with work by Widjaja et al. (2012) that recently began to quantify IT infrastructure heterogeneity, I take them as my starting point to account for the diversity of technologies in an IT infrastructure.

Several diversity indices have been suggested, relating closely to the concept of *entropy* (Lamberson and Page 2012; Schütz et al. 2013). Especially the Herfindahl index has long been a workhorse in economics, where it was used to assess industry concentration in markets or even to quantify religious homogeneity within local areas (Bothner et al. 2010; Page 2011). For market contexts, the Herfindahl index (*HI*) is written as the sum of firms' squared market shares. For a network consisting of elements of k types, *HI* writes as shown in Equation 4.2 such that

$$\mathrm{HI} = \sum\nolimits_{\mathrm{i}}^{\mathrm{k}} p_{\mathrm{i}}^{2} \tag{4.2}$$

where p_i is the probability that this type of outcome i is true and p_i^2 denotes the probability that if two elements would be selected at random from the distribution that both elements would be of the same type. The variable k is the number of types in the set of elements.

For reasons of clarity, I inverse the Herfindahl index which then brings us the inverse diversity index D as shown in Equation 4.3:

$$\mathrm{D} = \frac{1}{\sum_{\mathrm{i}}^{\mathrm{k}} p_{\mathrm{i}}^2} \tag{4.3}$$

The lower bound of the inverse diversity index is one if all types are equally likely and the upper bound is $1/k$.

I draw on a simple example from Page (2014) to illustrate the diversity index's mechanics. Suppose there are four types of outcomes, each of which have a probability of one-fourth of being true such that $A = ¼$, $B = ¼$, $C = ¼$, $D = ¼$. The diversity index now attempts to quantify how unlikely the different types of outcomes (p_A, p_B, p_C, p_D) are, given the system's current state. As only these four types of outcomes can happen, probabilities p_A to p_D have to add up to one. We want to discern *homogeneous* cases in which probabilities are one-forth, one-forth, one-forth, one-forth, in contrast to *diverse* ones with one-half, one-half, zero, and zero. Thus, we first compute the probability that if two elements interact, they are of the same type. Suppose this is a distribution over technologies used by organizations and there are four types A, B, C, and D. The probability that two random organizations use type A is now $p_A * p_A$ and so forth. The overall probability that two organizations use the same type of technology is then $p_A * p_A + p_B * p_B + p_C * p_C + p_D * p_D$. Suppose then we have $p_A = p_B = p_C = p_D = 1/4$. Then, the Herfindahl index becomes $(1/4)^2 + (1/4)^2 + (1/4)^2 + (1/4)^2 = 4/16 = ¼$. Thus, the diversity index is then 1 over ¼, which is equal to 4. As can be seen from the example, the upper bound of the diversity index is the number of types in the set. There are four equally likely types in the set.

As another example, taken from Page (2014), suppose, we have three types but they are not evenly distributed: $p_A=1/2$ $p_B=1/3$ $p_C=1/6$. Hence, the diversity index should be a little less than 3. This is because the system is not going to be as diverse as three types. The Herfindahl index is $(1/2)^2 + (1/3)^2 + (1/6)^2 = 14/36$. The diversity index hence is 36/14 or 2 4/7, which is less than 3.

So why does the **diversity index** serve as useful to measure lock-ins? The lower bound of the inverse diversity index is 1; as we are looking at stochastic, history-dependent processes, this situation describes a deterministic state in which only one type in the set has a positive probability of being selected. Thus, a diversity index of one would tell us that a system is in a state of lock-in (cf. Page 2006). As an example, suppose there are initially five types (e.g. technologies) an agent could select, but finally there is only one technology left: the diversity index would fall from 5 to 1. In a path-dependent system, one could observe a shrinking diversity index, e.g. from 5, to 4.8, 4.5, 4.3 to 1.2, and 1.0, showing a diminishing scope of agents' actions.

Network-adjusted Homogeneity

I further suggest a network-adjusted measure of homogeneity h_i which is determined for agent i according to Equation 4.4

$$h_{\mathrm{i}} = \frac{\sum_{\mathrm{j\ in\ N(g)}} x_j}{\mathrm{N_{ij}(g)}} \text{ with } x \in \{0{,}1\} \text{ and } 0 \leq h_i \leq 1 \tag{4.4}$$

where x_j is a binary variable that draws on the technological choice of i's neighbors. It is one if i's peer j also uses technology k, and zero otherwise. We sum over all neighbors of i. The measure is normalized by dividing it by the total number of neighbors (N_{ij}). The idea is that an agent's choice and switching probability is contingent on its embeddedness in a network. That is, how heterogeneous an agent's neighborhood is. Homogeneity h_i takes a value of one if i's reference group fully draws on technology k. In contrast, h_i is zero if none of i's neighbors adopts the technology used by i.

Network homogeneity H is calculated by averaging homogeneities over all individual agents as shown in Equation 4.5:

$$H = \text{average } (h_i) \ \forall \ i \in N(g) \tag{4.5}$$

Figure 15a gives a simple example in which each agent is adjacent to only neighbors of different quality: homogeneity is minimal. Figure 15b shows a configuration in which each agent is adjacent to only neighbors of the same type; homogeneity reaches a maximum and the configuration is supposed to remain stable in a game under strategic payoff complementarities in which agents adapt their action to their direct peers' behavior (cf. Jackson 2008b). Figure 15c also depicts a homogeneous situation. However, two technologies govern different clusters. We can mitigate concerns about distinguishing Figure 15b and Figure 15c by supplementary diffusion curve analysis (cf. Arthur 1989).

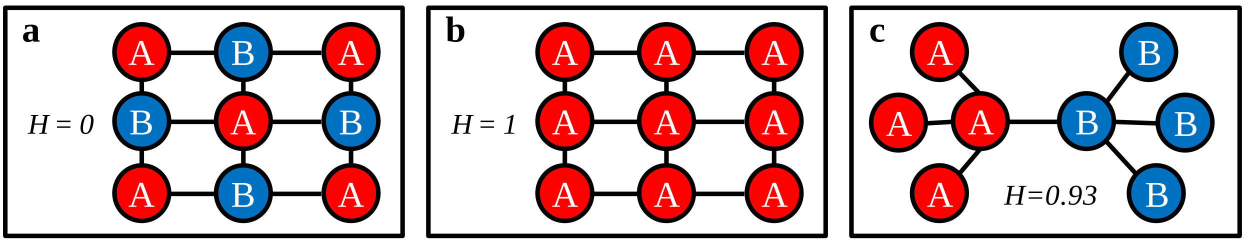

Figure 15. Examples for network-adjusted homogeneity measure

Individual Misfits

As I have introduced strategic agents that draw on individual inclinations ("standalone utilities") and network influences, another measure on the extent to which a system is locked in to a particular option is the extent to which agents' *actual* decisions misfit their individual preferences towards technologies (cf. Draisbach et al. 2013). To account for individual misfits, I define a binary variable $imisfit_i$ for agent i as shown in Equation 4.6 such that

$$imisfits_i = \begin{cases} 0, \ \textbf{if } a_i(k) = \max(a_{ki}) \\ 1, \ \textbf{otherwise} \end{cases} \tag{4.6}$$

where $a_i(k)$ is the realized standalone utility of agent i computed as a function of the technology k the agent actually selected. If a_i equals the maximum of the vector a_{ki} consisting of all standalone utilities to the agent, the chosen solution does fit its natural inclinations. Thus, $imisfits_i$ equals zero, and one otherwise. To determine the fraction of individual misfits over the entire network (*imisfit*), we average over agents' individual values.

4.3 Equilibria for Extreme Cases and Hypotheses

In this section, I derive some baseline results on the type of outcomes that should be expected under varying growth processes and I put forward several hypotheses for further experimental consideration.

4.3.1 Standardization Regimes

To best understand the impact of different growth parameters on standardization outcomes, it is useful to distinguish three regimes with respect to diversity in the network. The series of plots in Figure 16 illustrates these three regimes graphically:

I. *Chaotic regime:* I define cases in which none of the technologies is able to govern significant parts of the network as a *chaotic regime*. In such case, the diversity index is high as different technologies persist in the network but network-adjusted homogeneity is low as local neighborhoods remain diverse. From a central perspective, this situation is the worst as standardization benefits remain unrealized (Weitzel et al. 2006).

II. *Clustered regime (islands of shared technologies):* I define a situation in which different technologies spread cluster-internally as a *clustered regime*. Under a clustered regime, the diversity index is high as several technologies persist and network-adjusted homogeneity is also high as clusters grow internally coherent. Standardization benefits can be realized cluster-internally and gateway or converter technologies may enable the connection of the different clusters of a network (David and Bunn 1988; Hanseth 2000, 2002).

III. *One standard's dominance:* Complete standardization with one technology is defined as a regime of *one standard's dominance*. Diversity is low as one technology comes to dominate and network-adjusted homogeneity is high as local neighborhoods are homogeneous. Standardization theory suggests that such situation is often desirable as it enables synergies among agents (Buxmann et al. 1999; Weitzel et al. 2006); one standard dominance will, however, point to lock-in situations (David 1985; Arthur 1989).

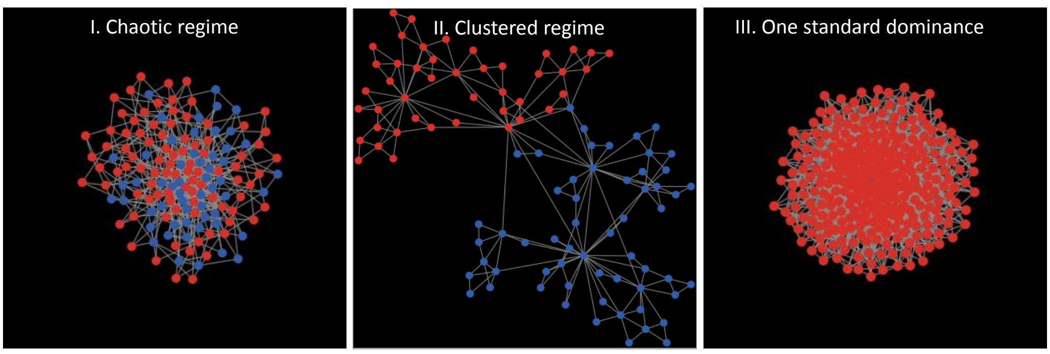

Figure 16. Standardization regimes: (I.) chaotic, (II.) clustered, and (III.) uniform

Chaotic and clustered regimes are usefully distinguished. First, both regimes differ in standardization benefits (Weitzel et al. 2006). The former is inferior by realized synergies from the standardization. Second, both regimes may require different network interventions (Valente 2012) to get out of lock-ins. While network-wide standardization in chaotic regimes requires solving a difficult coordination problem, network-wide standardization in clustered regimes may be achieved by gateways or converters (cf. Hanseth 2002).

4.3.2 Extreme Case Hypotheses

The two squares depicted in Figure 17 show how key parameters in my model – proportionality (p), degree of interaction (m), and preferentiality (α) – interact. The two squares' relevant corners (1.) – (6.) provide extreme cases for which I derive hypotheses for experimental consideration:

1. When the degree of interaction is low ($m = 1$) and link formation is preferential ($\alpha = 0$), the diffusion of different technologies in the network is likely: agents attach preferentially to one of multiple hubs giving rise to hubs growing over time. As technologies are assigned randomly to hubs at the initialization, a clustered regime with multiple islands of shared technologies (II.) should arise. Overall homogeneity in the network should be high as hubs grow internally-coherent, similar to the pattern depicted in Figure 15b.
2. When the degree of interaction is low ($m = 1$) and link formation is random ($\alpha = 1$), different technologies should spread in the network. Outcomes should be chaotic (I.) or clustered (II.) as new agents form chains of technologies with different lengths.
3. When the degree of susceptibility to network effects (m_{rel}) is zero, no global patterns will emerge as network effects are absent and agents' decisions depend fully on agents' natural inclinations, I expect a chaotic regime (I.) with different technologies to arise.
4. Refer to the former case (3.).
5. When the degree of susceptibility to network effects (m_{rel}) is close to one and each new agent connects to all other agents, I soon expect the network's tipping over to one technology; as interactions grow proportional to the network size, the growth process gives rise to positive feedback that reinforces one solution. In this case, a regime of one standards dominance should emerge (III.) as this case is structurally equivalent to the model of path dependence and increasing returns proposed by Brian Arthur (1989).
6. Refer to the former case (5.).

If m, the number of links formed, is an absolute number for each new agent, m may be larger than the network size n in any considered time period. The right side in the left rectangle then corresponds to the cases (5.) and (6.) of the proportional model in which all available states of other agents are processed by the new agent. As a consequence, I left empty the right side of the first square because both cases then yield identical outcomes.

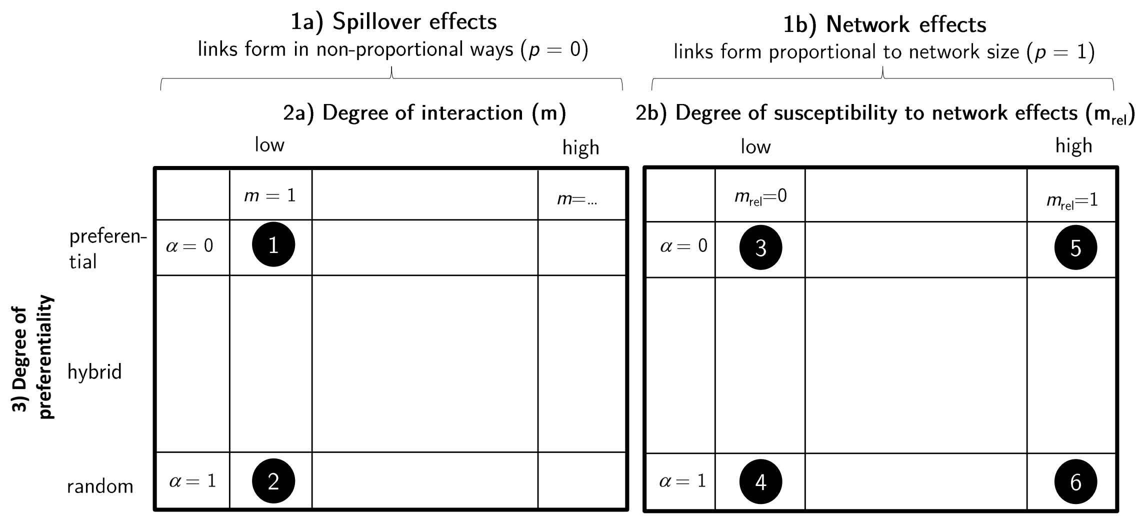

Figure 17. Interaction of key parameters

4.3.3 Hypotheses on Effects of Growth on Diversity

My objective is to test the effects of growth on IT infrastructure diversity. I introduced the diversity index and network-adjusted homogeneity as two useful measures of diversity. I will now discuss hypotheses along the lines of research on network and spillover effects.

Positive feedback in standard diffusion processes can reinforce the dominance of the most-diffused technology (Shapiro and Varian 2008). The mechanisms are a greater creditability of a standard with more adopters, and the availability of complementary products and services (Hanseth 2000). The underlying notion of network effects has been made operational in previous models by assuming that an agent's payoff is a function of the network size (Weitzel et al. 2006). If we portray a network of n agents – each adopting one of the k technologies – we can recast network effects in the terminology of network formation: each period, one agent i_1, i_2, i_3, and so forth enters the scene and forms links to existing agents. Each of these links provides i information on technology k. As the network grows over time, network influences also grow: the number of links in t_1, t_2, t_3... grows *proportional* to the network size. Under such growth process, the increasing benefits of adopting the most-diffused technology may unleash a positive feedback spiral that eventually locks in one technology (Arthur 1989). Arthur's (1989) model of path dependence is most illustrative to underline my main argument: if agents entering the network become influenced by any other agent in the network and their presence exhibits positive externalities on any other agent, more and more agents will be drawn towards the most-diffused solution over time, creating a situation of positive feedback in which network influences outweigh individual preferences to a larger and larger extent. In other words, variety decreases and eventually only one of several options remains. I expect this scope-diminishing effect to be strongest, when influence from the network is strongest.

Recent work on diffusion has focused on direct spillovers between agents (Aral et al. 2009; Borgatti et al. 2009). As a starting point, many of these models have thereby assumed fixed capacities to link to friends, or generally interaction partners. This may be close-knit dyadic partnerships, triadic of friendship ties or interactions in larger communities (Borgatti et al. 2009). If we conceive new agents' decisions of whom to interact with as a problem of link formation, these models assume a *fixed number of links* – one at minimum – being formed independently of the network size. Hence, we can say that link formation is *non-proportional*. Traditionally, diffusion models have showed limited interest in systemic phenomena such as path dependence and have been more concerned with analyzing dyadic or triangular relationships (Borgatti et al. 2009). The limited extent to which these models look into systemic diffusion of technologies, however, suggests *more diverse* patterns with respect to technologies in use as a result of the network structure (cf. Aral et al. 2009).

Taken together, I suspect that it is useful to distinguish growth processes under (*proportional) network effects* and (*non-proportional) spillover effects*. As the latter limits the amount of network influences on a new agent, I propose that:

Hypothesis 1: *Spillover effects and network effects influence diversity differently.*

In many situations, the number of interactions will become increasingly large. For instance, IT systems such as airline inventory systems have technical (and business) interfaces to several dozens or even hundreds of other systems. Taking into account the pervasiveness of situations in which new nodes in a network tend to connect to a large number of other nodes, I am interested in whether growth under (non-proportional) spillover effects tends to approximate – in the limit – standard diffusion outcomes for network effect-driven growth processes. I suspect that situations in which new agents link to an absolute number of partners (*non-proportional growth*) will often produce similar outcomes to situations in which the number of partners is a function of the network size (*proportional growth*) if the number of partners becomes sufficiently large. As an extreme case, the number of absolute links exceeds the network size in every considered time period which makes non-proportional growth equivalent to proportional growth. Then, both growth procedures should produce outcomes in which diversity decreases to its minimum level as one of several standards comes to dominate the network (Arthur 1989; Leydesdorff and van den Besselaar 2000). I thus suspect that:

Hypothesis 2: *Increases in the degree of interaction lead to decreases in diversity.*

Finally, I am interested in the influence of varying network influence strengths on diversity. Generally, there is a straightforward relationship between the strength of network influences and diversity: the stronger the network influence, the lesser value an agent places on his or her natural inclinations, and hence the more susceptible the agent is to the network influences, which results in an increasing number of instances in which agents decide against their base preferences (cf. Arthur 1989). Hence, the number of individual misfits (or “personal lock-ins“) should increase with increasing network influence strengths (cf. Draisbach et al. 2013). If we assume that an equal share of agents with two different types populate a network, in a situation of lock-in, half of the agents should decide against their natural inclinations. The higher the number of individual ”lock-ins“, the lower the diversity in the network, as agents would start to select only one particular technology even though they may fancy another one (Draisbach et al. 2013). This effect should be strongest if the network is densely connected, as a lower density in the network should limit the extent of network influences (Draisbach et al. 2013).

Hence, I expect the degree of interaction – which may be viewed as a measure of the network's density – to moderate the effect of varying network influence strengths on diversity. I thus propose that:

Hypothesis 3: *As the degree of interaction increases, an agent will be more adapt to varying network influence strengths, thus increasing the effect of network influences on diversity. Hence, diversity will decrease to a higher extent with increases in degrees of interaction.*

Chapter 5

Insights from Agent-based Simulations: Growth

5.1 Computational Implementation of Growth Model

I implemented the growth model in Netlogo 5.0.3, an agent-based simulation platform (Wilensky 1999). Refer to code example oS3 in the online supplements. Netlogo provides a, Logo-based, high-level programming language to create and run agent-based models; the platform itself is mostly written in Scala (and Java); I selected the platform as it features predesigned components such graphical prototyping that allows the creation of plots, monitors, and other design elements instantaneously, and provides agent-communication mechanisms, an integrated software tool for performing experiments, and various extensions for debugging, performance measurements, and so forth (Gilbert and Troitzsch 2010; Gilbert 2008). These features were particularly useful during the early phases of the project as they allowed for rapid exploration of model variations; in addition, a significant user-community provides several useful extensions and agent-models. For instance, I utilized the network extension that allowed to draw on predefined network structures, primitives, and measures (Netlogo 2014). As shown in Figure 18, my implementation featured not only the quantitative analysis with respect to monitoring predefined heterogeneity and network measures on the macro level and plotting their development over time, but also enabled a visual analysis of the micro and segment-level[13] outcomes of my model. I was therefore able to interact more intensely with the model.

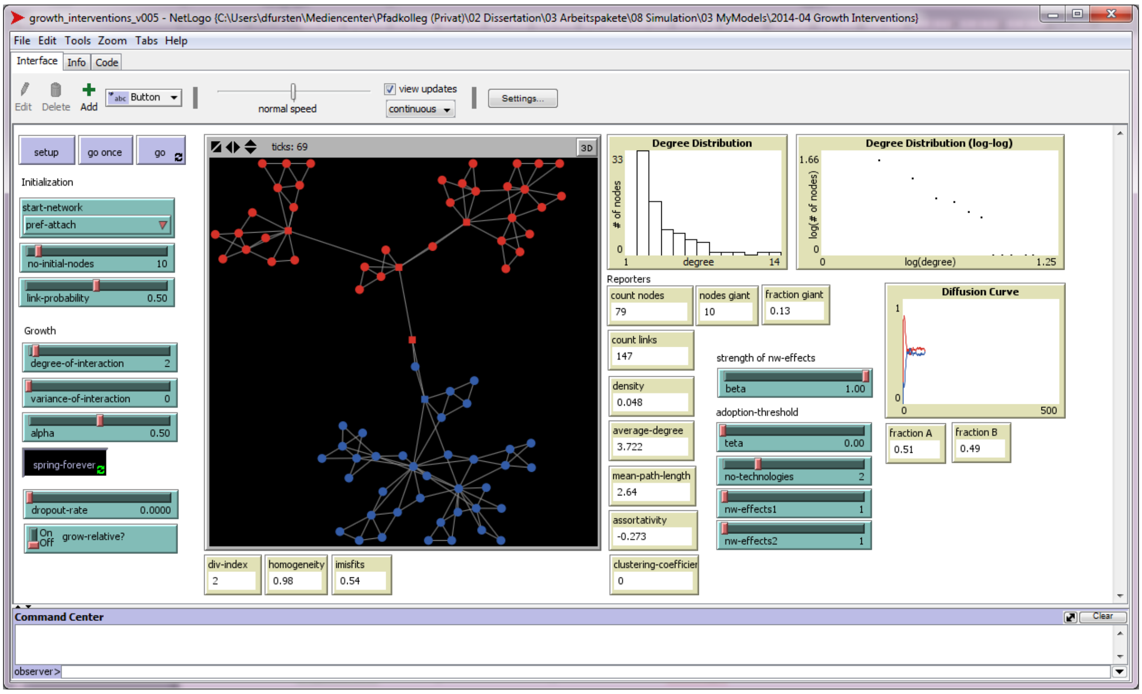

Figure 18. Implementation of the growth model in Netlogo

[13] Drawing on a distinction by Valente (2012), I refer to the *micro level* as status of individual nodes, e.g. whether they adopt or not; by *segment level*, I refer to status of groups, clusters, or other sets of nodes.

Scratching a platform would have required programming most of these prepackaged components by myself; while the final model may have been faster and more scalable if I programmed the model using a (native) integrated development environment such as Eclipse or Visual Studio (computing times for large instances with 10,000 or more nodes often exceeded one week at the high-performance cluster of Freie Universität Berlin), I worried about insufficient support for graphical analysis, rapid model prototyping, and experimentation.

5.2 Theoretical Validation and Verification

This section derives some baseline results for particular parameter constellations demonstrating that the model is able to replicate findings of well-known existing models such as the Polya Process and the model of path dependence by Brian Arthur (1989).

5.2.1 A Network without Network Influences

A first set of simulations aimed at showing the system's behavior in situations in which network influences are absent. We expect to see a diverse network with technologies being distributed randomly across agents. I chose the experimental setup as follows (refer to Table S7, Exp. 1): as in Arthur's model of path dependence (1989), I assumed two types of agents (R and S from the set ν) adopting two types of technologies (A and B from the set k). I assumed that newly-created agents belong to either group with equal probabilities. Fixing the strength of the network effects to zero ($\beta = 0$) and initializing a preferential attachment network with 10 nodes in which we assigned technologies uniformly at random, the network grew 300 periods.

A quick look at the series of network plots shown in Figure 19a-c points instantly to the main finding: for a setting in which network influences are absent and agents' preferences are balanced, the network growth process does not matter. Both technologies become adopted by an equal fraction of agents. Figure 20 shows the outcome of a typical run in which I also set agent's base preferences to zero ($a_{RA} = a_{RB} = a_{SA} = a_{SB} = 0$).

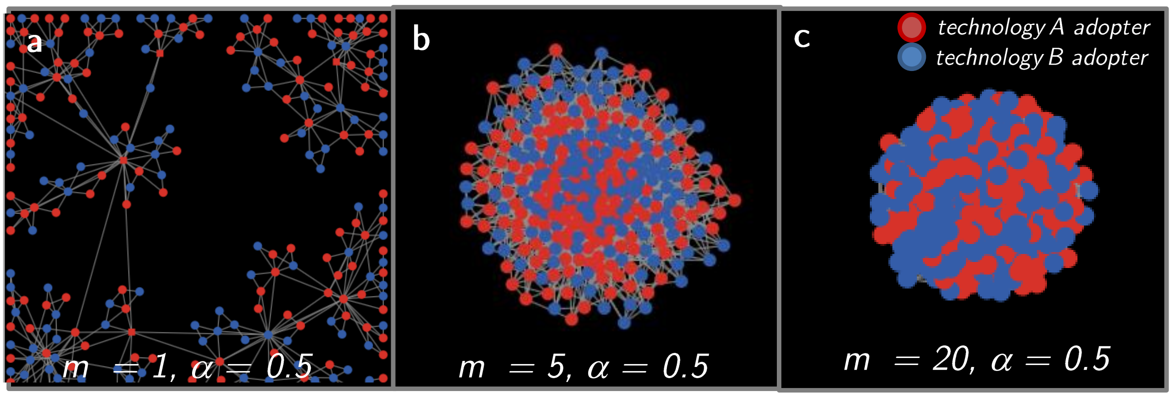

Figure 19. Diffusion of technologies in absence of network influences

This figure shows three samples of the simulation for varying degrees of interaction (m). The figure depicts in all cases the situation after 300 periods. We see that the density of the graphs varies considerably but the diffusion outcome – the distribution over colors – is always diverse.

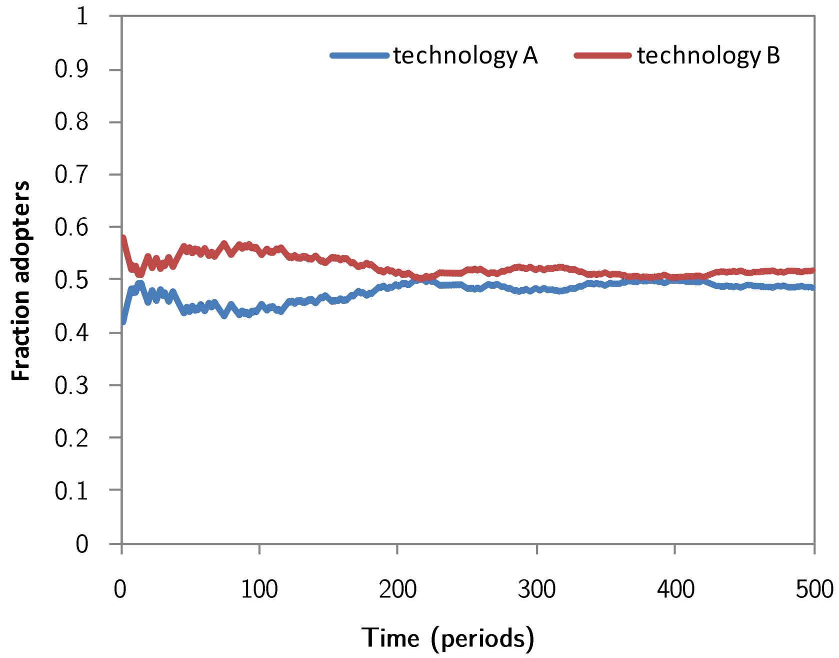

Figure 20. *Sample run for a process without network influences*

This figure shows one sample run of a process without network effects in which both technologies become adopted by almost equal fractions of agents. I set the degree of interaction to a medium level (m = 5) fixing medium degrees of preferentiality (α = 0.5).

5.2.2 Replicating the Model of Path Dependence by Arthur (1989)

I set up further experiments (refer to Table S7, Exp. 2-6) to reproduce characteristic findings of Brian Arthur's model of path dependence and increasing returns (see Arthur 1989). While my model is more general with respect to varying a system's growth logic, the model's outcomes should correspond to that of Arthur's model for particular parameter constellations. As Arthur's original model is analytical while I use a stochastic simulation, I have to average results over multiple runs to show correspondence (Gilbert and Troitzsch 2010).

As a first step, I show qualitatively that the model can produce diffusion patterns similar to those of Arthur's model (1989:120): agents eventually turn to one of two technologies. In the long run, the system settles on one of multiple fix-point attractors. In other words, "the observer must predict A's share either as 0 or 100%" (Arthur 1989:121).

I draw on a hybrid random process assuming that new nodes attach to existing nodes in the network. Consequently, one cannot start with a clean state as the first node entering the network must attach to another node. To remain close to Arthur's model, I start with the simplest possible initialization process: I create a network of two connected nodes. I assume that node i_1 has adopted technology A and node i_2 adopted technology B. By doing so, I assure that the process is *unbiased* (Page 2006:101), excluding cases in which the process tends deterministically to one equilibrium as the absorbing barrier is already passed before the observation is started (refer to Algorithm A.1).

Drawing on Leydesdorff and van den Besselaar (2000:15), I set usual ratios for standalone utilities ($a_{RA} = a_{SB} = 0.8$, $a_{RB} = a_{SA} = 0.2$) and network multipliers ($b_R = b_S = 0.1$). In Arthur's model, growth occurs relative to the network size. For technology A, in particular, the agent's choice is influenced by all existing adopters of technology A (n_A) and for technology B the agent is influenced by all adopters of technology B (n_B). To receive this network externality, a new agent needs to connect to all n existing agents in the network N increasing linear with t. Hence, I set up a proportional growth model where the number of links each new agent forms – which I denote as m_{rel} (its susceptibility to network effects) – equals one. The agent is fully connected to all other agents (the agent takes into account the feedback from each group of technology adopters depending on the technology assessed). The degree of preferentiality (α) is set to one because any bias towards higher degree nodes – as it is the case for any degree of preferentiality unequal to one – would mischaracterize Arthur's model. As agents, however, form links to all existing agents in the network, the findings should be insensitive to different levels of preferentiality (refer to Table S7, Exp. 2 for the setup).

The diffusion curves in Figure 21, which show absolute differences in adoption between both technologies, illustrate my main finding here: the model enabled me to reproduce Arthur's analytical findings – dominance of one technology in the long run and the passing of an absorbing barrier – by the means of simulation. In the five runs depicted, I observed that the system always tipped towards one of the technologies.

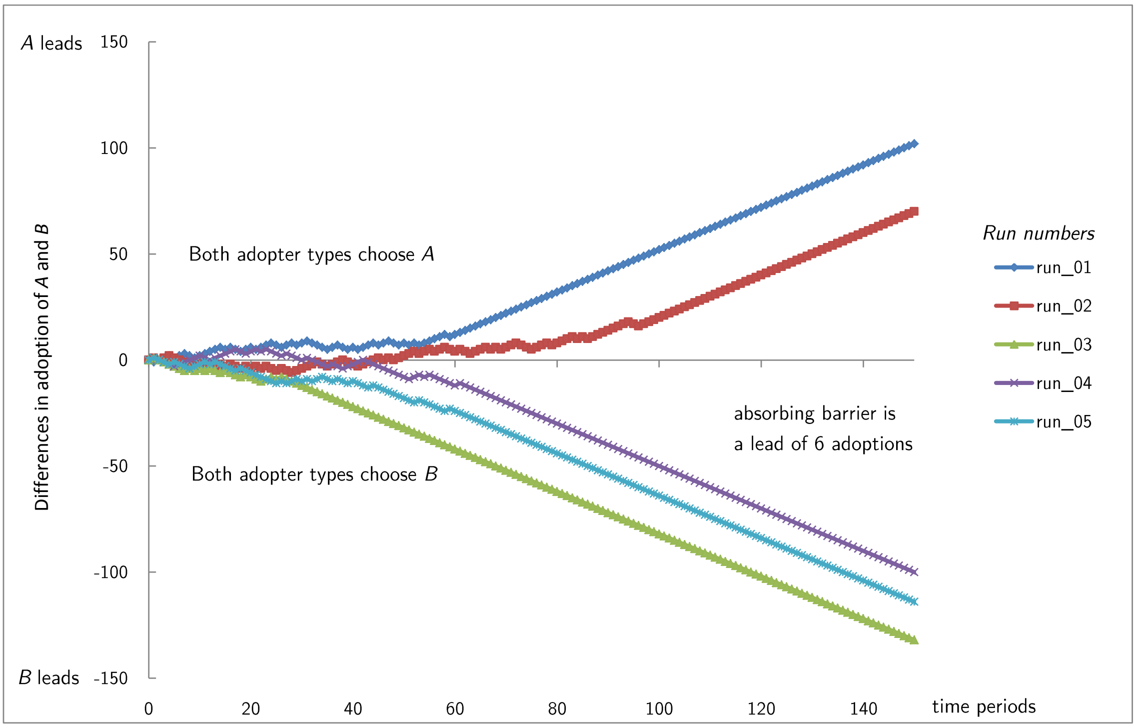

Figure 21. Absorbing barriers in samples replicating Arthur's path dependence model

This figure shows the difference in adoption for five sample runs with medium network multipliers ($b_R = b_S = 0.1$) fixing agents' base preferences to 0.8 and 0.2 for both agent types respectively. For each run, I recorded the fraction of adopters for each technology and computed the absorbing barrier according to Arthur (1989:120). I plotted the absorbing barrier as a straight line in the figure.

As shown in Figure 22, the expectation that one of two technologies comes to dominate could be confirmed: The system converged to a share of either 0 or 100% A-adopters.

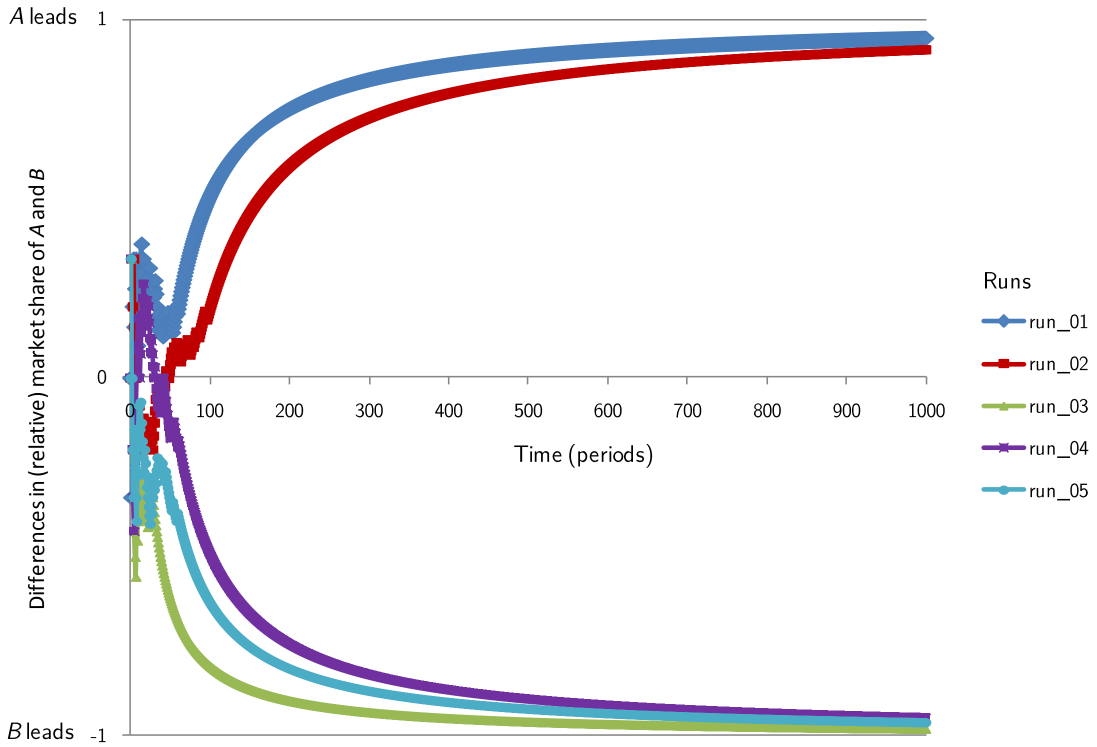

Figure 22. *Sample runs for processes replicating Arthur's model of path dependence*

This figure shows diffusion outcomes for five sample runs with medium network multipliers ($b_R = b_S = 0.1$) *fixing agents' base preferences to 0.8 and 0.2 for both agent types respectively.*

Next, I carried out batch simulations to test whether the model produces outcome patterns as expected from Arthur's path dependence model in different dimensions using the several measures of diversity introduced earlier: (*i*) diversity (D), (*ii*) the fraction of individual misfits (*imisfits*), and (*iii*) network-adjusted homogeneity (H). I now restate them briefly and discuss my expectations on what values these measures should take in a model reproducing Arthur's model of path dependence.

Diversity (*i*) assesses the likelihood of particular types of outcomes to occur. This is achieved by adding the squared probabilities of occurrence for all types of outcomes (and then inversing it). Diversity tends to one, if one type of outcome is very likely while all other outcomes are very unlikely. Diversity tends to its upper limit – the number of outcome types – if each type is equally likely. Diversity in Arthur's model should tend to one as one set of outcomes (the 'winning' technology) becomes very likely over time and all other outcomes become very unlikely.

The *fraction of individual misfits* (*ii*) assesses the extent to which agents make a choice that corresponds with their "natural preference" (Arthur 1989:111). In a simple model, agents' preferences tend either towards technology A or technology B. If an agent's choice misfits his or her natural inclinations and the agent is drawn to the other technology because of network influences, this agent is flagged as "individually locked in" (Draisbach et al. 2013). The fraction of individual misfits reports the percentage of individually locked in agents in the network. The fraction of individual misfits should tend to 0.5 in Arthur's model as both agent types (*R*-agents and *S*-agents) are equally likely to turn and in the long run half of the agents should have an incentive to turn to the leading technology (cf. Arthur 1989:120).

Network-adjusted homogeneity (*iii*) takes into account the extent to which agents in the network are surrounded by peers adopting the same technology. An individual agent's homogeneity tends to one if an agent only has neighbors that chose the same technology as it. Homogeneity is zero if the agent is alien in its neighborhood; only surrounded by agents using a different technology. Overall homogeneity is then defined as the mean over agents' individual homogeneities; it should tend to one as one technology is expected to gain a market share of 100%. Consequently, each agent should be surrounded only by peers adopting the same technology.

Refer to Table S7 (Exp. 3-5) for the complete experimental setup. Table 12 summarizes the results: I found that the model closely matched my expectations with respect to all the measurement dimensions discussed above. In particular, I found that the model was robust against increases in the network multiplier by two orders of magnitude. Increasing the network multiplier to $b_A = b_B = 1.0$ and $b_A = b_B = 10.0$ yielded qualitatively the same results as for $b_A = b_B = 0.1$. At a very low level of the network multiplier ($b_A = b_B = 0.01$), the outcomes, however, balanced to an equal share of both technologies as both adopter types mainly realized their preferences; in this case, the absorbing barrier was never passed within the time limit.

Table 12. Results for different network effect strength with two technologies

Exp.	Network multipliers ($b_R = b_S$)	Diversity	Std. dev.	Fraction misfits	Std. dev.	Homogeneity	Std. dev.
1[1]	0.1	1.056	0.033	0.475	0.020	0.948	0.028
2[1]	1.0	1.006	0.006	0.499	0.016	0.996	0.006
3[1]	10.0	1.006	0.010	0.500	0.015	0.996	0.010
[1] Average results for 100 simulation runs; time limit was set to 1,000 periods							

To test robustness with regards to increases in the number of technologies, I set up further experiments in which I increased the number of technologies to five (refer to Table S7, Exp. 6). I also increased the number of types of agents to five. Each agent type preferred one technology ($a_i = 0.8$) while all other technologies appeared inferior to the agent ($a_{i\text{-}1} = 0.2$). I started with a network of five fully-linked nodes, each of which adopted one of the five technologies.

Figure 23 shows the results for a typical level of the network multiplier, setting it symmetric across agent groups ($b_{1\,=\,\ldots\,=}\,b_5 = 0.1$). We see the path-dependent nature of the process quite clearly. After an initial phase of contingency, one technology gains momentum and subsequently the fraction of adopters rises constantly to a level close to one.

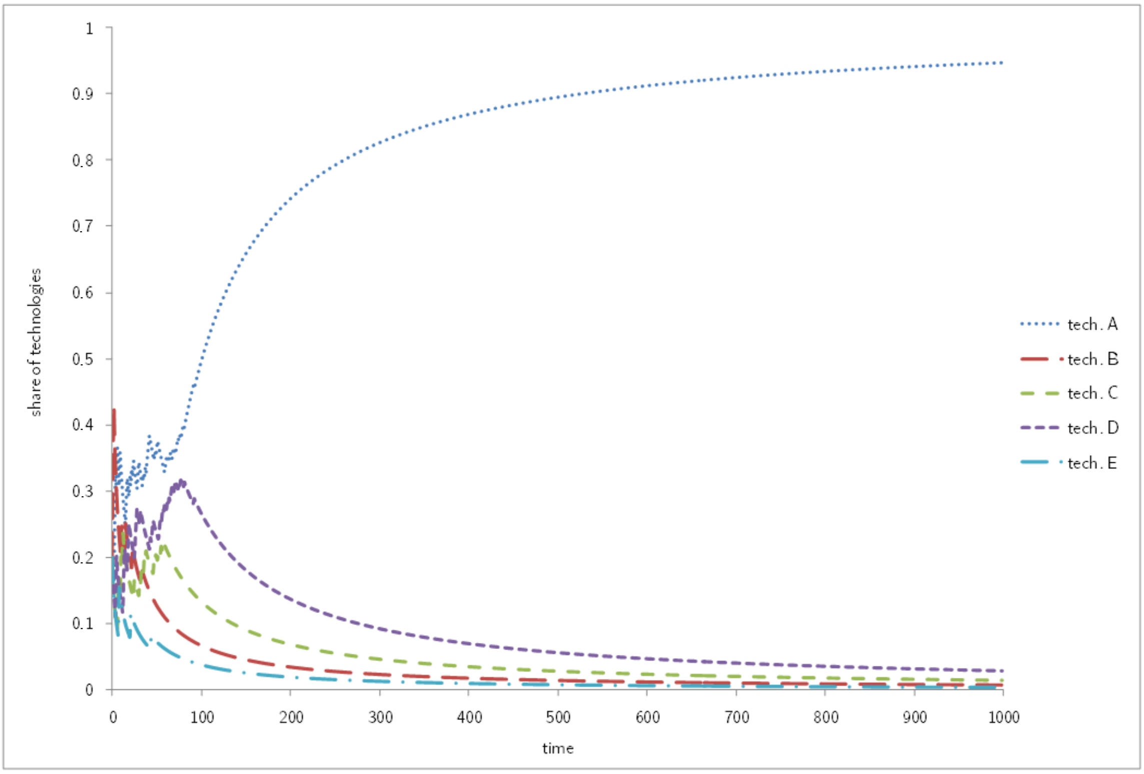

Figure 23. *Diffusion curves from one typical run with five technologies*

Table 13 shows numerical results at this level of the network multiplier: as expected, diversity took a value close to the minimum of one, the network-adjusted homogeneity approximated a level close to one, and the fraction of individual misfits approximated a level of (1 – 1/5 = 0.80). Essentially, findings were robust for increases in the number of technologies with respect to diversity, network-adjusted homogeneity, and the fraction of individual misfits.

Table 13. *Robustness for a model with five technologies*

Exp.	Nw. multiplier ($b_1 = b_2 = ... = b_5$)	Number technologies	D	Std. dev.	imisfits	Std. dev.	H	Std. dev.
4[1]	0.1	5	1.120	0.047	0.749	0.0216	0.895	0.037
[1] Average results for 100 simulation runs; time limit was set to 1,000 periods								

5.2.3 Replicating the Polya Process

A third set of theoretical experiments aimed at verifying the model against the backdrop of the Polya Process. The Polya process is a seminal example of a path-dependent process as it aptly captures several characteristic features of path dependence such as non-ergocity and equilibrium-dependence, as well as the phenomenon of increasing returns (cf. Arthur 1994; Page 2006). Drawing on a version by Page (2006:98), I define the Polya process as a process in which an urn initially contains one brown (B) and one maroon (M) ball and if a brown ball (resp. a maroon) ball is selected it is put back with another ball of the same color (Page 2006:98). The Polya Process is expected to converge to *any* ratio of balls (Page 2006:98; refer to chapter 2.4.2).

I model the Polya Process as a *proportional* growth process in a network in which new agents enter sequentially (one at a time). Each new agent links fully to all other agents in the network. To reproduce the Polya Process, I modify the growth model by adapting the agents' payoff function (cf. Equation 4.1) to account for the fact that agents will not maximize their utility with respect to technological choices but that they select technologies according to the ratios by which these technologies are currently distributed within the network. These ratios can be understood as selection probabilities. Thus, let p_k designate the probability that technology A or B from the set k is selected according to Equation 5.1, such that

$$p_k = \sum\nolimits_{i \text{ in } N(g)} x_k \; / \; (n - 1) \tag{5.1}$$

where x_k is a binary variable and $x_k = 1$ if agent i has selected technology k, and $x_k = 0$ otherwise; $(n - 1)$ is the number of other agents in the network (excluding the agent that just entered). Let rd designate a random variable where $rd \in \mathbb{R} \mid 0 \leq rd \leq 1$. In the simple case of two technologies A and B, a new agent $i*$ then adopts a new technology A or B from the set k – indicated by a switch in the binary variables x_A or x_B from zero to one – according to the adoption function as shown in Algorithm A.6. The mechanics of the approach are straightforward: Line 3 calculates the selection probability p_A for technology A. Then, in line 4, a random number rd between 0 and 1 is drawn. If p_A is smaller or equal to that number, technology A is selected, otherwise technology B. Thus, in line 5 one of the technologies is selected according to the current distribution in the network, denoted by the binary variables x_A and x_B.

Algorithm A.6 Adoption function in Polya Process with $k = 2$ technologies

I assume that p_A is a real-valued variable initialized as $p_A = 0$ for each agent and x_A and x_B are Boolean variables designating whether the agent adopts technology A or B

1: **for** agent $i*$ **do**
2: $\mathrm{x_A} := 0$, $\mathrm{x_B} := 0$
3: $\mathrm{p_A}$:= **sum** [x_A] **of** other nodes / **count** other nodes
4: rd := *random-float 1*
5: **if** $rd \leq p_A$ **then** $x_A := 1$ **else** $x_B := 1$ **end if**
6: **end for**

For $k > 2$ technologies, we have to compute the selection probability p_k for each technology k in the network. Then, we think of the selection probabilities as places in a unit interval from zero to one of different span-with. The first place spans from zero to p_1, the second from p_1 to $p_1 + p_2$, the third from $(p_1 + p_2)$ to $(p_1 + p_2 + p_3)$, and so forth. For all k, p_k adds up to one, as each new agent has to select one technology. Creating a random digit rd in the interval from zero to one, agent $i*$ then selects one technology k by checking in which of the k places rd falls. If $rd \leq p_1$, $i*$ selects technology A, if $p_1 < \underline{rd} \leq (p_1 + p_2)$, $i*$ selects technology B, if $(p_1 + p_2) < rd \leq (p_1 + p_2 + p_3)$, $i*$ selects technology C and so forth.

The Polya Process can then be replicated by setting the parameters of the model as follows (refer to Table S7, Exp. 7): first, I turn off agents' base preferences and consider a situation in which only network influences matter (β = 1). Second, I fix the number of agent types ν to one (ν = 1) as base preferences are non-existent and network effects are identical across agents. Third, I fix the network multiplier to one (b = 1) as for each ball drawn from the urn exactly one more ball is added in the next period. Forth, I modify the agents' original adoption function (refer to Algorithm A.5) by replacing the decision rule from lines 15-16 ("adopt the technology with the maximum payoff") with the new decision rule from Algorithm A.6 ("adopt technologies according to their selection probability").

Given the increasing returns-nature of the process, I then want the network to converge to one particular ratio of technologies. As an important feature of the Polya Process, I expect that each run settles to one specific distribution over outcomes differing across runs (e.g. 80:20, 73:27, 60:40, and so forth). Furthermore, I expect that the process will not show considerable fluctuations over the run time once one regime has settled. Hence, diffusion rates and diversity are expected to remain stable over the time of the observation.

The series of plots a-c in Figure 24 give support to the expectation that diffusion rates remain stable once a particular regime has come to dominate. A quick look at the structure of each plot gets quickly to the main analytical finding: the processes converge to a particular fraction of technology adopters. As expected, diffusion rates differ from run to run as a function of early events within the process. I also found consistent results indicating a stabilizing diversity level.

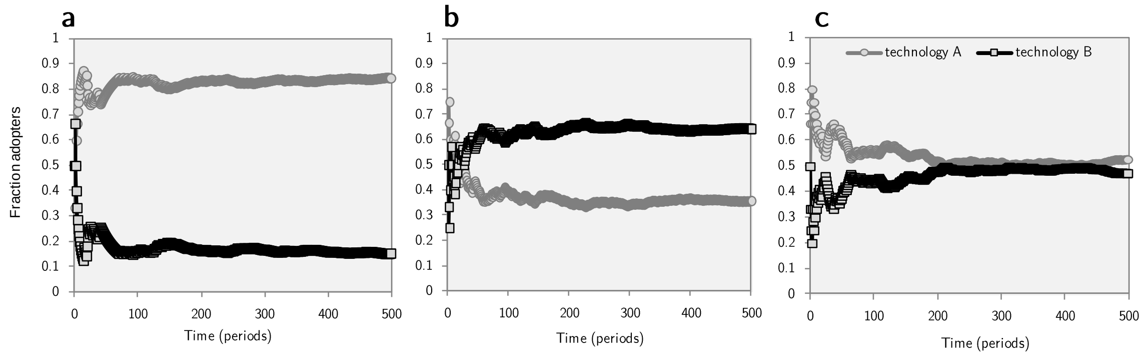

Figure 24. *Three sample runs of the growth model replicating a Polya Process*

5.2.4 How Inertia Builds Up

I next analyze visually how inertia builds up for varying degrees of interaction (m). Fixing the degree of preferentiality to hybrid (α = 0.5), Figure 25 shows typical network plots.

We see that there is a remarkable difference between low degrees of interaction (m = 1) and increasing it to a high level (m = 7): while clustered patterns emerge for low degrees of interaction, the network lumps together for high levels. At a low degree of interaction (refer to the series of plots a-c), we also see the influence of preferentiality quite clearly. While all nodes gain links over time as a result of the hybrid growth process, central nodes gain above-average numbers of links. These hubs grow in importance as a function of their age and their above-average degree, which reinforces their importance over time. Furthermore, the average path length grows as a function of time as a number of nodes attach to peripheral nodes without connections to distant locations in the network. This is a result of the fact that, for this degree of interaction, nodes cannot form other links than to one close partner.

The series of plots in Figure 25d-e turns our attention to high degrees of interaction (m = 7). As a result of the interdependency between various elements, the network is dense in contrast to the former case. The network's average path length tends to a low value as almost all nodes are connected. Therefore, high degrees of interaction point to a situation in which changes in each element require complementary changes in an increasingly larger number of other elements.

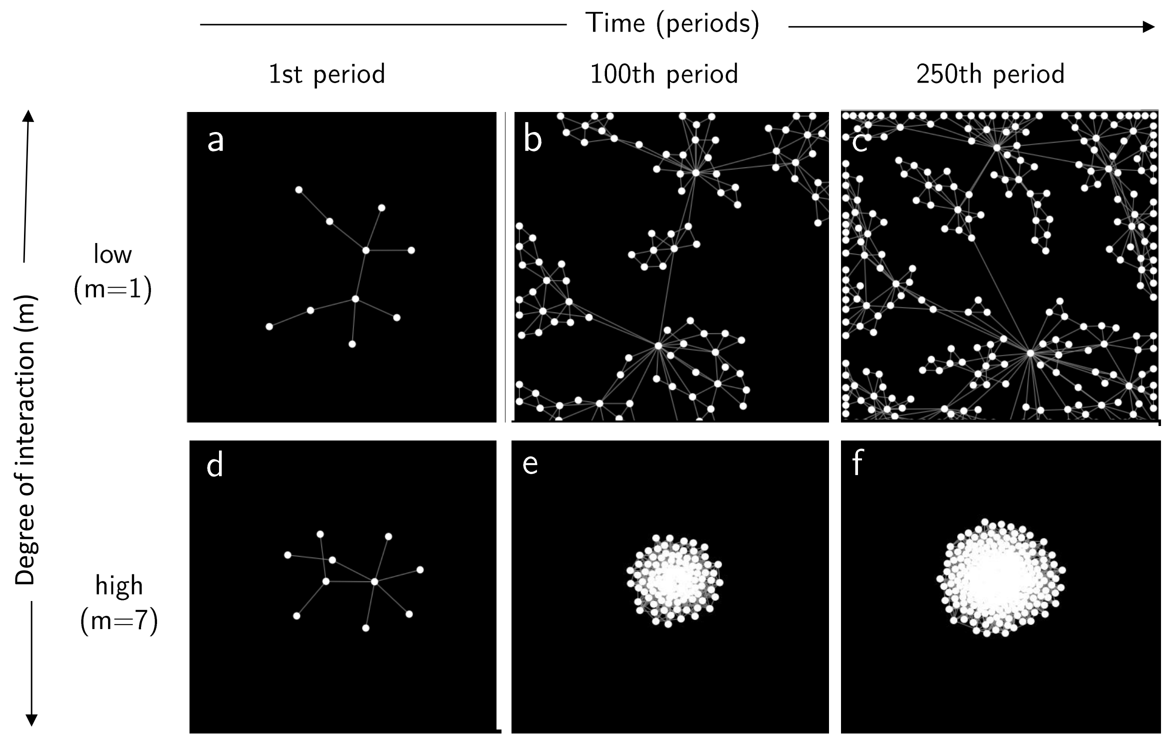

Figure 25. *Growing networks with a varying degree of interaction (m)*

5.3 Results: Standard Diffusion in Growing Networks

I now turn to a first set of main results. These concern how diversity in the network depends on the degree of proportionality (p), interaction (m), susceptibility to network effects (m_{rel}), and preferentiality (α).

5.3.1 Network Effects and Spillover Effects Are Usefully Distinguished

The first hypothesis proposed a difference in the diversity in settings with network effects and spillover effects. For the simulations, I assume a full-density network with n = 35 initial nodes. Following the guidelines by Law (2007:500-505), I set the time limit of the simulations to 500 periods. Based thereupon, I performed two sets of experiments (refer to Table S7, Exp. 8-9): one set of experiments considered proportional and one non-proportional growth. Under non-*proportional growth* (p = 0), I work with varying degrees of interactions (m) between 1 and 20 (increasing it in increments of 1); under proportional growth (p = 1), I vary the degree of susceptibility to network effects (m_{rel}) between 0 and 1.0 (increasing it in increments of 0.1). For the experiments, I fixed the degree of preferentiality (α) to a level of $\alpha = 0.5$. Agents selected one of $k = 2$ technologies according to the adoption function in Algorithm A.5.

My first exercise concerns proportional growth ($p = 1$) for varying the degree of susceptibility to network effects (m_{rel}) while holding all other variables fixed. Results are shown in Figure 26a: excluding the extreme case of $m_{rel} = 0$ as well as cases in which $m_{rel} > 0.5$, the figure shows how diversity varies with typical levels of m_{rel}. I excluded cases in which $m_{rel} > 0.5$ as diversity did not decrease any more compared to a level of $m_{rel} = 0.5$. From the plot, we see that diversity peaks at 1.2 for $m_{rel} = 0.1$ and then further decreases for higher levels of m_{rel}. Refer to the appendix, Table S8, for numerical results.

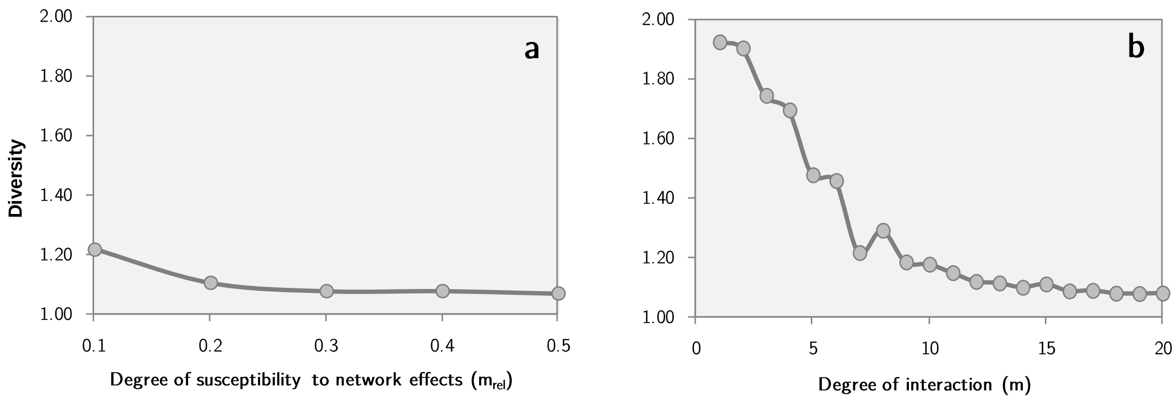

Figure 26. Effects of proportional versus non-proportional growth on diversity

A second set of experiments (refer to Table S7, Exp. 9) concerns non-proportional growth processes ($p = 0$). In this connection, Figure 26b spots the impact of growth with varying degrees of interaction (m) on diversity. Varying degrees of interaction give us all outcome regimes: when m is very low, $m = 1$ or $m = 2$, diversity always remained at a level close to a value of 2. At that level, an equilibrium with two technologies persisted in the vast majority of instances: clustered regimes emerged. For medium ranges of m ($m \in [3, 4]$ and $m \in [5, 6]$) diversity dropped to a range of 1.4 to 1.7. Standard deviations in this range were high compared to the other cases. At that level, the system either remained in a diverse state in which multiple technologies persisted or tipped more towards one technology.

From Figure 27 (cf. movie oS1), a plot of typical sample runs with (a) spillover effects and (b) network effects, we get to the main finding: in figure (a), with spillover effects and low degrees of interaction ($m = 2$), several standards persist and clustered regimes settle in separate parts of the network. The overall configuration stabilizes at a particular rate of diversity. In figure (b), with network effects, diversity decreases. One standard settles.

Viewed together, Figure 26a and Figure 26b are important because they highlight salient differences between proportional and non-proportional growth.

For non-proportional growth (refer to Figure 26a), I observed three distinct regimes: a *clustered regime* (II.) in which multiple technologies persist in different clusters of the network, a *chaotic regime* (I.) in which limited network effects are not strong enough to tip the entire network in one direction within a limited time frame, and a regime of *one standard dominance* (III.) in which one technology came to dominate the entire network.

Limited overlap between proportional (i.e. network effects) and non-proportional growth (i.e. spillover effects) suggest that these growth processes are usefully distinguished. As can be seen in Figure 26b, proportional growth fosters one standard's dominance (III.).

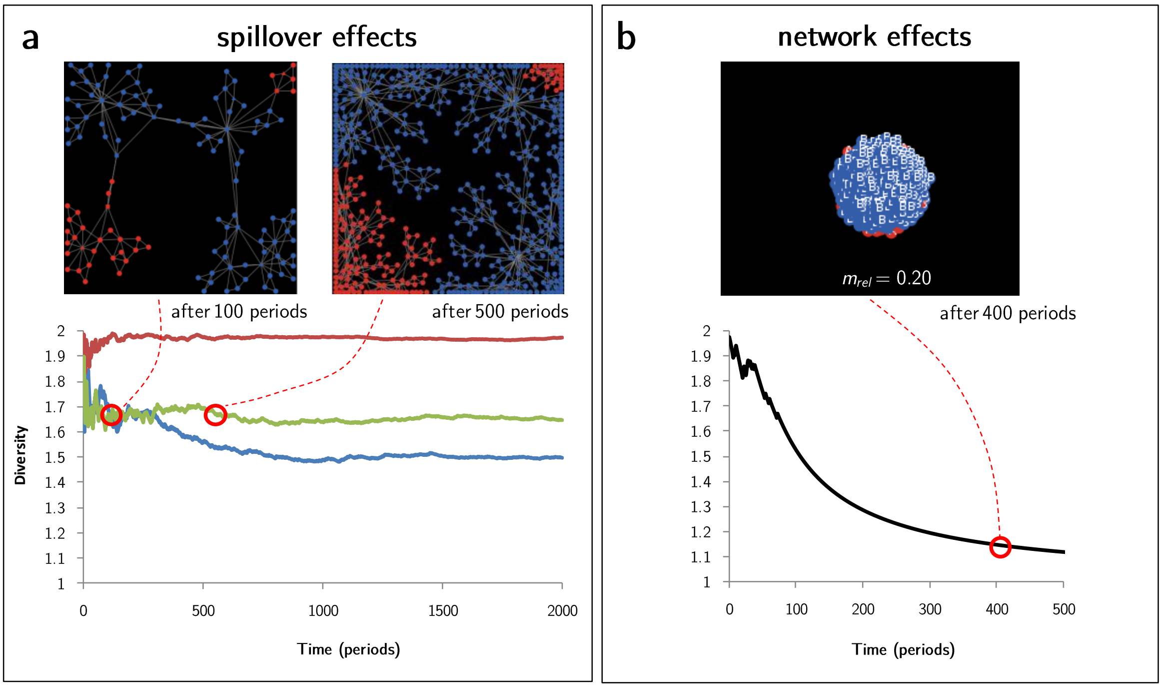

Figure 27. *Distinguishing spillover and network effects*

This figure shows how diversity develops in settings with (a) spillover effects and (b) network effects. In figure (a), I depict three runs of the simulation with low degrees of interaction (m = 2) for a non-proportional growth process (α = 0.5). In figure (b), I depict one sample run for a low degree of susceptibility to network effects (m_{rel} = 0.2).

Additional Analysis for (Proportional) Network Effects

Exploring the peak in mean and standard deviation for $m_{rel} = 0.1$, I performed further experiments varying m_{rel} between 0 and 0.3 in increments of 0.025 (refer to Table S7, Exp. 10). Figure 28 shows the impact for various values of m_{rel} on diversity.

We see a non-monotonicity quite clearly. When m_{rel} is sufficiently low, 5 percent or below ($m_{rel} < 0.05$), we then see that diversity is above 1.2. At that level, a number of cases exist in which two technologies persist in the network. As m_{rel} increases (in the range starting from 0.05 or above), the network settles to one technology in the vast majority of cases. Decreases in the standard deviation of D – refer to Table S9 in the appendix – indicate a decreasing number of instances in which multiple technologies persist for increases in m_{rel}.

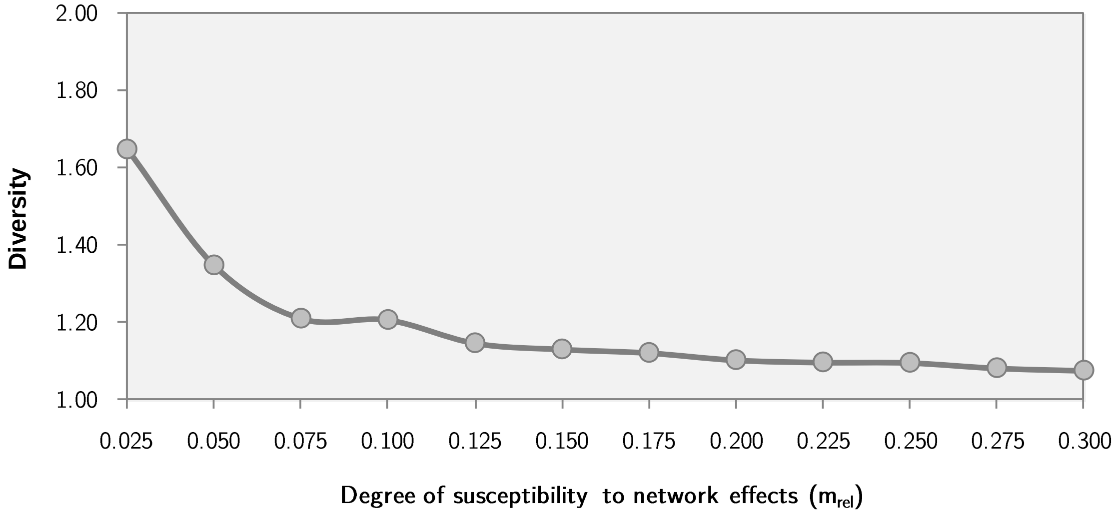

Figure 28. *Extended results for effects of proportional growth on diversity*

This figure shows diversity as a function of various degrees of susceptibility to network effects (m_{rel}) varying it from 0.025 to 0.3 in increments of 0.025. The number of links formed by a new agent grows thus proportional to the network size.

Additional Analysis for (Non-Proportional) Spillover Effects

Considering diverse outcomes for medium ranges of m in more detail, I turn to a detailed analysis of the micro level processes. Consider in this connection the series of plots as depicted in Figure 29. This figure shows how diffusion patterns emerge for varying degrees of interaction (m). For each run, I initialized a preferential network with 10 nodes diffusing technologies from hubs (refer to Algorithm A.2). Fixing preferentiality to hybrid (α = 0.5), I grew the network for 150 periods. Fixing the strengths of the network influences to the highest level ($\beta = 1$), agents could choose between 2 technologies (A and B). Hence, agents relied only on influences from the network and had no natural inclination in any direction.

Figure 29a turns attention to low degrees of interaction (m = 1). From the figure, we see that several clusters emerged that were uniform in their technological choice. In Figure 29b –d, I depict several runs in which I set the degree of interaction to a medium level (m = 3). We see that the system converges to varying fractions of adopters. In fact, I found the system behaved as a Polya Process as particular clusters of the network that turned to particular technologies became more and more uniform as can be seen in Figure 29b in the bottom region. Figure 29e depicts the consequences of increasing the degree of interaction to a high level (m = 7). We see that a tipping towards one technology occurred. I observed that this became increasingly likely with increases in the degree of interaction (m).

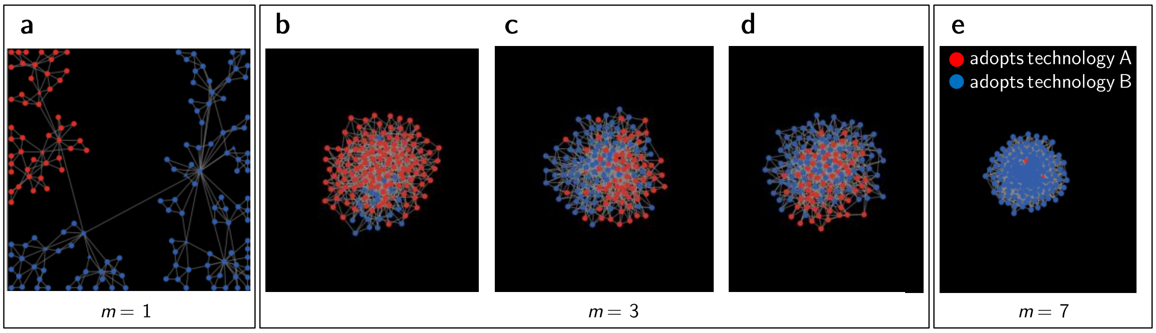

Figure 29. Clustering for varying degrees of interaction (m) in sample networks

Figure 30 shows typical diffusion curves when focusing on a medium degree of interaction ($m = 3$) and keeping all other variables fixed. Consistent with the series of plots in Figure 29b-d, we see that the system converges to a particular fraction of adopters after an initial period of contingency. The figure shows that this outcome pattern will most likely not be a situation in which one standard comes to dominate but that diverse or clustered regimes settle.

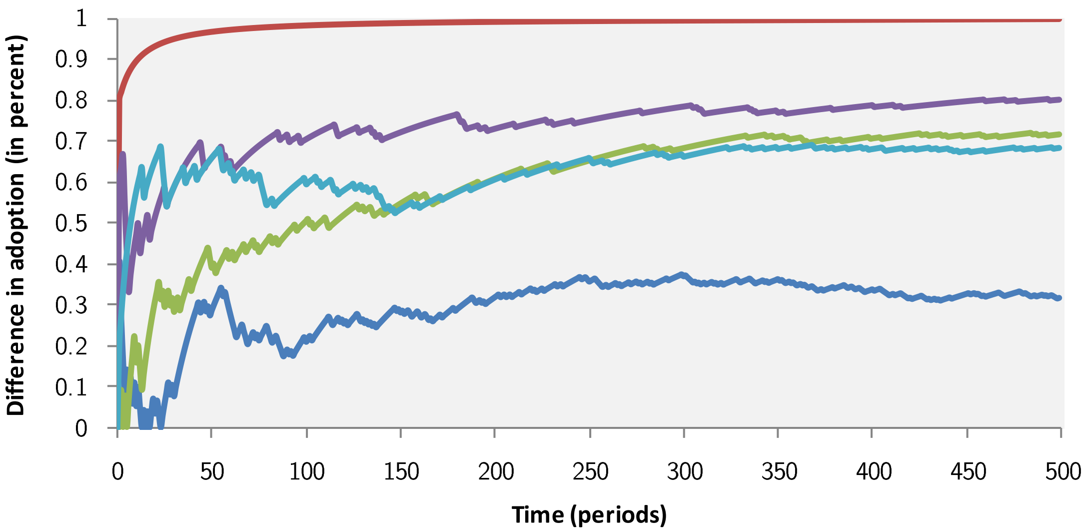

Figure 30. Sample runs with medium degree of interaction for hybrid growth process

5.3.2 Diversity Decreases with Increasing Degrees of Interaction

In the second hypothesis, I was interested in the effect of varying degrees of interaction (m) on diversity (D). I operationalize diversity by the inverse diversity index D. To test this relationship (refer to Table S7, Exp. 13), I varied the degree of interaction (m) and the degree of preferentiality (α), fixing the model to non-proportional growth. Following Law (2007:500-505), I set the time limit of the simulations this time to 1,000 periods.

Table 14 shows how diversity varies with m and α. When m is low ($m = 1$), diversity tends to a medium level of 1.5 or above. Higher levels of m correspond to lower levels of diversity. This finding is robust across preferential ($\alpha = 0.0$), hybrid ($\alpha = 0.5$), and random ($\alpha = 1.0$) ways of link formation. From Table 14, we see an increasing number of cases where one solution comes to dominate the network with increases in the degree of interaction (m). I hence find support for the proposition that increases in the degree of interaction lead to decreases in diversity (refer to Figure S4 in the appendix for the complete set of results for varying m and α).

Table 14. Diversity (D) as a function of interaction (m) and preferentiality level (α)

	Degree of interaction (m)					
	Low ($m = 1$)		Medium ($m = 3$)		High ($m = 7$)	
Degree of preferentiality (α)	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Preferential ($\alpha = 0$)	1.58	0.37	1.09	0.20	1.01	0.02
Hybrid ($\alpha = 0.5$)	1.53	0.35	1.26	0.34	1.01	0.03
Random ($\alpha = 1$)	1.58	0.32	1.08	0.19	1.01	0.02

Decreases in diversity for increasing degrees of interaction become obvious when we look at the series of plots in Figure 31: the more partners an agent interacts with, the more likely it is for a single standard to dominate the network.

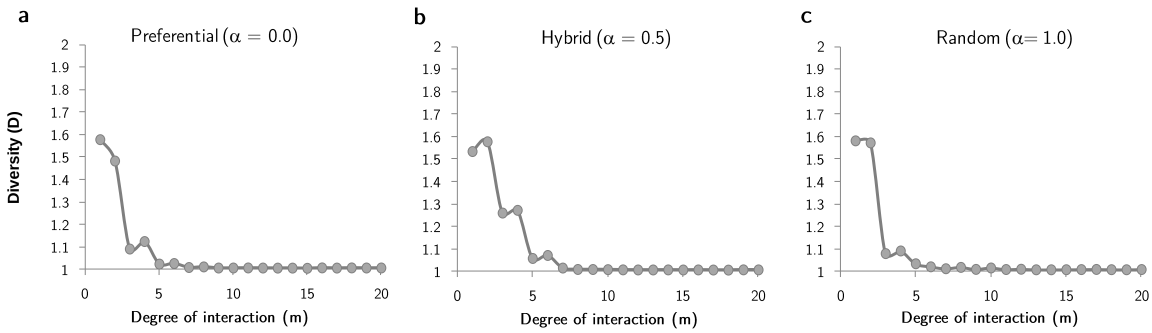

Figure 31. Effect of interaction (m) on diversity (D) for varying preferentiality (α)

This figure shows diversity (D) as a function of varying degrees of interaction (m), fixing the degree of preferentiality to (a) preferential (α = 0.0), (b) hybrid (α = 0.5), and (c) random (α = 1.0). The network grew for 1,000 periods; results averaged over 100 runs.

My next exercise is to assess how varying degrees of interaction (m) and preferentiality (α) affect network-adjusted homogeneity. Drawing on the setup from Exp. 13 (refer to Table S7), Figure 32 shows the impact of non-proportional growth for various degrees of interaction (m) and preferentiality (α) on network-adjusted homogeneity (H).

The main analytical finding is straightforward: when m is sufficiently low, $m = 2$ or below, homogeneity is highest with values close to 1. At that level, a local optimum is reached. For high levels of m, with m at levels of 7 or above, the network again approximates the limit value of $H = 1$. This configuration results in a *U-shaped* relation between degrees of interactions and homogeneity. Two mechanisms are at work: for high *m,* network influences boost homogeneity with respect to one standard's dominance (III.) while a *clustering effect* works for lower *m.* New agents attach preferentially to hubs promoting coherent clusters of different technologies (II.). Refer to Figure S5 in the appendix for the complete set of results for varying m and α.

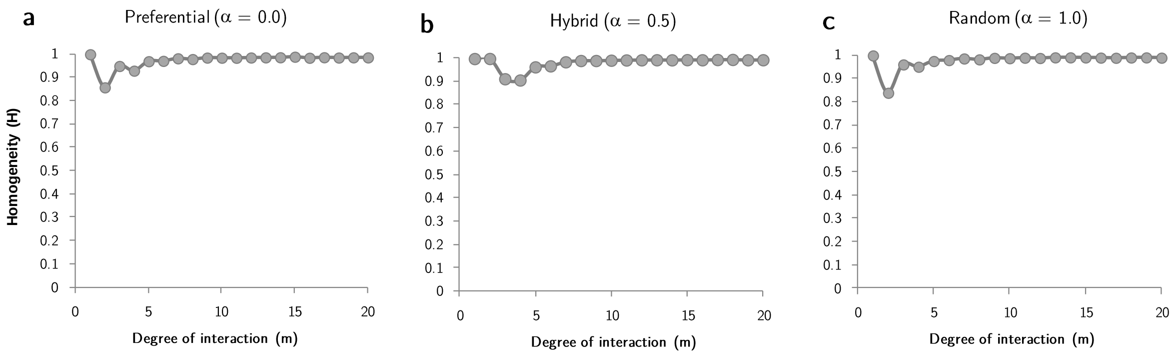

Figure 32. *Effect of interaction (m) on homogeneity (H) varying preferentiality (α)*

5.3.3 The Consequences of Varying Network Influence Strength

In the third hypothesis (H3), I was interested in the effect of varying network influence strengths (β) on diversity (D), moderated by the degree of interaction (m). A next set of experiments thus combines these two factors, β and m, to test their effect on diversity.

My first exercise is to vary the network influence strength (β) and the degree of interaction (m), fixing preferentiality at a medium level (α = 0.5). I used the preferential attachment strategy with k = 2 technologies to initialize the network (refer to Table S7, Exp. 11). The network grew for 1,000 periods.

Figure 33a-c shows how diversity varies with β and m. We see a non-linearity at almost every degree of interaction: Higher network influences, β = 0.5 and above, result in diversity remaining at a high level (two is the maximum diversity for k = 2 technologies). Essentially, agents can realize their natural inclinations and multiple technologies persist in the network. As expected, stronger network influences result in lower levels of diversity. As shown in the figure, this proposition holds for all levels of m but the relationship is least pronounced for low degrees of interaction (m = 1). As shown in Figure 33a, networks with medium (m = 3) and high degrees of interaction (m = 7) switch suddenly from a chaotic, multi-standard regime (I.) to a one standard dominance regime (II.). In contrast, Figure 33b shows that for low degrees of interaction (m = 1), the system's diversity will not fall to a minimum level but plateaus at a medium level. With low degrees of interaction, islands of shared technologies emerge (III.). Refer to Figure S6 in the appendix for more detailed results where I increased the degree of interaction (m) from 1 to 7 (in increments of 1). Viewed together, I hence find support for the moderator hypothesis that diversity will decrease to a higher extent with increases in degrees of interaction.

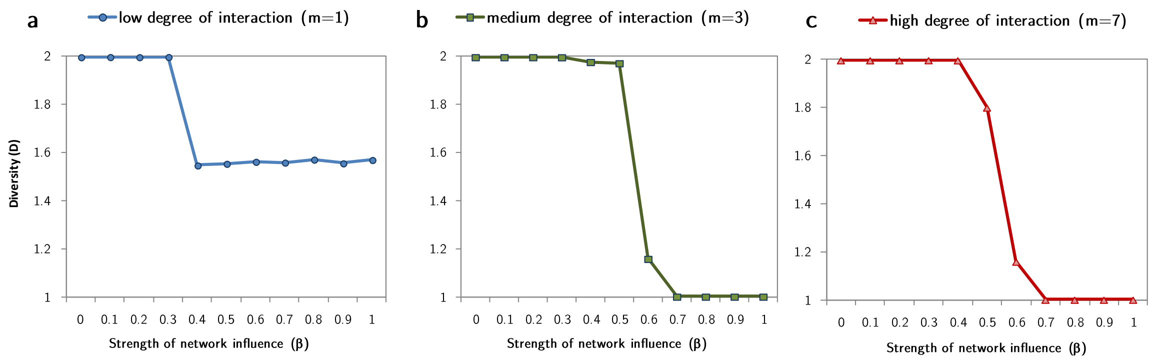

Figure 33. Effects of network influence (β) on diversity (D) varying interaction (m)

This figure shows how diversity (D) decreases as a function of the network influence strengths (β) for varying degrees of interaction (m). On the right-side, for medium and high degrees of interaction (figure b and c), we see an almost immediate drop in diversity from a high to a low level. For high network influence strengths, agents realize their preferences and above a certain threshold level, agents' natural inclinations lose importance and sooner or later, one standard comes to dominate. For low degrees of interaction (figure a), however, the decrease is less pronounced and particular technologies can come to thrive in different areas of the network.

Table 15 shows numerical results for low ($m = 1$), medium ($m = 3$), and high degrees of interaction ($m = 7$) and the varying strength of network influences. We can see that standard deviations vary strongly: while standard deviations of zero point to cases in which one regime settles deterministically – for instance for low network influences ($\beta = 0$) where a multi-standard regime (I.) always emerges – other cases in which standard deviations vary drastically are less obvious to interpret. Consider for instance a situation in which network influences are maximal ($\beta = 1$) and the degree of interaction is low ($m = 1$). We have considered this case already in the former experiments. In this instance, a *clustered regime* (II.) emerged and the results on standard deviations show that results often vary significantly with respect to the ratios with which both technologies come to diffuse in the network.

Table 15. Effects of network influence (β) and interaction level (m) on diversity (D)

Diversity[1,2]	Degree of interaction (m)					
	Low ($m = 1$)		Medium ($m = 3$)		High ($m = 7$)	
Nw. influence (β)	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
β= 0	2.00	0.00	2.00	0.00	2.00	0.00
β= 0.3	2.00	0.00	2.00	0.00	2.00	0.00
β= 0.5	1.55	0.33	1.97	0.06	1.80	0.37
β= 0.7	1.56	0.31	1.00	0.00	1.00	0.00
β= 1	1.57	0.33	1.00	0.00	1.00	0.00

[1] Refer to Table S7, Exp. 11 for the experimental setup
[2] Average results for 100 simulation runs

Additional experiments (refer to Table S7, Exp. 12) showed that the findings were robust for varying the network initialization strategy (from preferential attachment to a minimal set strategy). The moderating effect of the degree of interaction (m) on diversity for low to medium levels ($1 < m < 5$) was, however, less pronounced.

5.3.4 Summary of Findings

Table 16 summarizes the main findings of the experiments. In the next section, I discuss important limitations and implications.

Table 16. Summary of findings from agent-based simulations

Hypothesis	Reference	Support	Answer
Spillover and network effects influence diversity differently	Aral et al. (2009); Arthur (1989); Beck et al. (2008); Fichman (2004)	yes	Strong susceptibility of growing network to lock-ins for all levels of network effects. Spillover effects limit network effects; "islands of shared technologies" become more likely.
Increases in interaction degrees lead to decreases in diversity	Arthur (1989); Leydesdorff and van den Besselaar (2000).	yes	Growing networks in which influences spill over across nodes directly become increasingly susceptible to lock-ins to one standard for higher degrees of interaction.
Network influence strengths mediate effect of spillover and network effects on diversity	Arthur (1989); Draisbach et al. (2012, 2013)	partial	No difference for situations of low network influences; agent's decide according to base preferences. For high levels of network influences, clustering effect when spillovers are present; lock-in under network effects.

5.4 Discussion and Preliminary Conclusion

5.4.1 Interpretation

Based on a simple model of standard diffusion among standard-adopting agents, I have examined the influence of interaction patterns in a growing network on diversity. The model sets itself apart from previous models by incorporating a unique network growth strategy: I combined a hybrid random growth model, featuring "friends-of-friends"-based partner selection in proportional and non-proportional ways, with strategic agents.

My contribution over Draisbach et al. (2013) is as follows. First, I incorporated different new growth logics and tested their effect on diffusion outcomes. I showed that standardization outcomes are contingent upon whether a system grows driven by network effects (proportional) or by spillover effects (non-proportional), and on the extent of interaction and preferentiality with which new agents form links to existing agents. Second, I added different initial network forms (i.e. preferential attachment networks, centralized and decentralized structures) as well as two initialization procedures and tested the effect on standard diffusion.

Analytical and experimental results highlighted several important features. Firstly, proportional and non-proportional growth is usefully distinguished as having different, non-monotonic effects on standardization outcomes: the dominance of a single global standard (III) is most likely under proportional growth as the number of interaction partners grows relative as a function of the network size, which makes new agents more and more likely to adopt the most-diffused standard (cf. Figure 26a). Reproducing the model of path dependence, as proposed by Brian Arthur (1989), increases confidence in my model's finding. Secondly, increases in the degree of interaction (m), increase the likelihood of one standard's dominance (refer to Figure 31). There is, however, an interesting trade-off on how the degree of interaction affects homogeneity. The trade-off results in a situation where middle ranges are the most diverse (refer to Figure 32). These results could be explained by clustered regimes with islands of shared technologies (II) that arise as a function of the network's non-proportional growth process.

5.4.2 Discussion: Islands of Shared Technologies and Their Implications

I believe that distinguishing chaotic regimes (I), islands of shared technologies (II), and one standard's dominance (III) – presents a useful reference point for theory building on different forms of standardization patterns. Figure 34 provides a summary of how I define these three states with respect to diversity and network-adjusted homogeneity. The most important square in this figure is the theoretical notion of "islands of shared technologies". I define them as a situation in which network-wide diversity is high, as multiple technologies persist, but diversity in local neighborhoods (in my terminology, network-adjusted homogeneity) is also high as local neighborhoods grow homogeneous. An important feature of "islands of shared technologies" is that these clusters became inert over time as new elements attach preferentially to clusters, such that they grow increasingly homogeneous. Not unlike the Polya Process, a particular distribution over outcomes settles over time whereas this ratio can vary significantly contingent on the network initialization and early events in the process.

Existing research on standard diffusion has so far only distinguished multi-standard persistence and the seminal path dependence case in which one technology comes to dominate a network. My contribution over Weitzel et al. (2006) is that I showed that diverse "oligopolies" differ with regards to local homogeneity. As the Polya Process, "islands of shared technologies" exhibit all characteristics of a path-dependent process (i.e. equilibrium-dependence and non-ergocity). Consistent with David (1994), these results show that multi-standard situations often persist: different technologies come to dominate in particular clusters of a network which boosts the misfit costs for ill-fitting new elements.

As a result of my investigation, path creation strategies may consider different roads based on the logic that governs a system's growth: While chaotic regimes (I) may require more traditional intervention strategies that aim at switching particular groups of agent's towards one standard (Weitzel et al. 2006), if one finds a system moving towards islands of shared technologies, one may rather aim at (a) consolidation, or (b) establishing appropriate gateway or converter technologies that allow for smooth interactions between different clusters (Hanseth 2000, 2002). Switching entire clusters may often require substantial efforts as these clusters may have accumulated significant resources and network effects within the cluster may impede transitions towards a common standard.

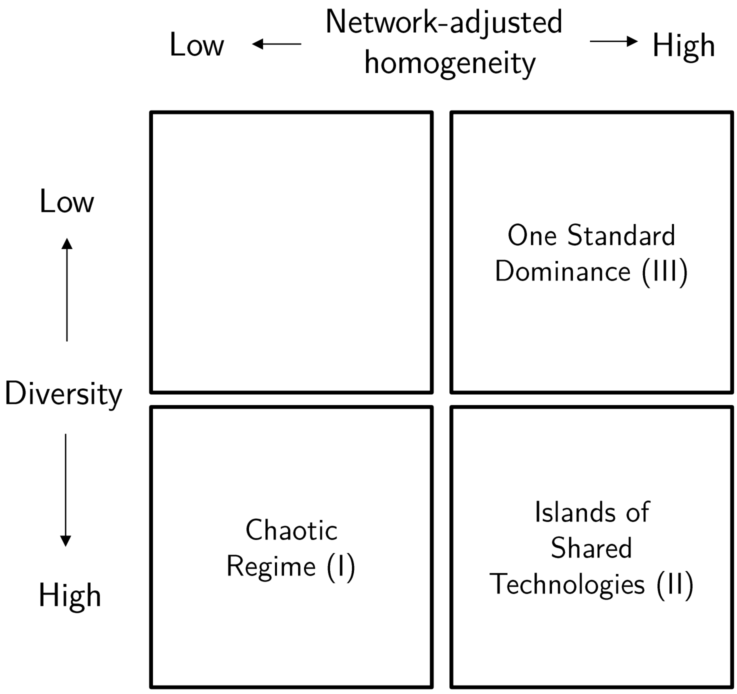

Figure 34. *Outcome regimes with respect to diversity and network homogeneity*

5.4.3 Limitations: Beyond Undirected Links, Rationality, and Irreversibility

I point to three important limitations. Firstly, I limited the analysis to undirected links. I believe that assuming mutual relations between nodes was a reasonable starting point in the model, as new nodes decided only once and irreversibly on which technology to use when they entered the network; the model could, however, mischaracterize situations in which nodes are related in indirect ways and changes are not limited to the moment of network entry.

Consider the series of plots in Figure 35. In Figure 35a, I refer to a situation in which two nodes are jointly dependent on each other: if one element is changed, then changes in the other element are triggered, as if two connected IT systems share the same data standards and one system is updated. For clarity, think of the link between inventory and revenue management systems by booking classes (Bartke 2013:20): optimization results from revenue management are fed back into booking limits in the inventory, new bookings then again become input for revenue management forecasting and optimization and so forth. Expert interviews, for instance, suggest that changes in revenue management components are only of limited value if results become thereafter transformed again in the restricted booking class format (refer to expert statements in oS2, oS7, and oS8). Even more alarming, Figure 35b portrays a situation in which two elements are not directly connected in mutual ways but via a third party. Think of additional interdependencies of airlines with GDS creating an indirect dependence where fare data from the inventory (i_3) is published to the GDS (i_1) that is in turn quoted by revenue management components (i_2) for forecasting and so forth. The reddish color indicates potential constraints that arise from the fact that the GDS are outside the influence of any particular airline and thus changes require potentially protracted negotiations (refer to expert statement in oS10). Incorporating such indirect dependencies has not yet been realized in the model and requires, at least, a recasting of the approach to account for incoming and outgoing links as described by Jackson and Rogers (2007).

Figure 35. Interlocking of (a) two and (b) three connected nodes

Two additional limitations are the assumption of rational decision making by strategic agents and also the irreversibility of decisions that limits the approach to settings with high sunk investments. In general, organizations will have limited switching points but assuming complete irreversibility may often be too restrictive.

5.4.4 Future Directions: Combining Network and Spillover Effects

I emphasize three promising ways to proceed further. Firstly, further work could combine non-proportional and proportional growth. Non-proportional growth captures well direct, contagious influences in a close-knit circle of connected agents (e.g. individuals, organizations, or organizational units). Underlying mechanisms of influence-based contagions have been described in Table 1: conformism, peer pressure, learning from the experiences of others, or information contagion. Proportional growth portrays another important process: agents' large-scale information processing intelligence on the global state of a market (or any other system of connected agents). The underlying mechanisms have been depicted in the standard reinforcement cycle in Figure 5: a larger installed base fosters more complements being produced, which enhances the credibility of a standard, which in turn biases decision-making of individual agents towards the dominant standard.

Few studies have combined influence-based contagion and network-size dependent effects to discern, which parts of the variance in standardization processes are captured by either of the effects. Figure 36 presents an important departure point in in this direction. The figure depicts a useful way to think about combining proportional and non-proportional growth: network influences may not grow linearly with the network size as a joint, hybrid function (e.g. polynomial) of the standard's total diffusion rate in the network and local influence processes. Combining both processes could help to explain extra-local patterns in the adoption of standards; especially those that require time to unfold installed base advantages.

Secondly, as noted by the economist Matthew Jackson (2008b), it is not only important to understand how particular networks form but also why they form. The focus of my approach was to present a model explaining how important empirically observable phenomena such as 'islands of shared technology' can arise. I utilized a hybrid random growth model and combined it with strategic agents, selecting technologies based on explicit cost-benefit considerations. I see it as a valuable initial vantage point towards further strategic models of link formation that go beyond assuming that some initial links are formed uniformly at random (cf. Figure 13a).

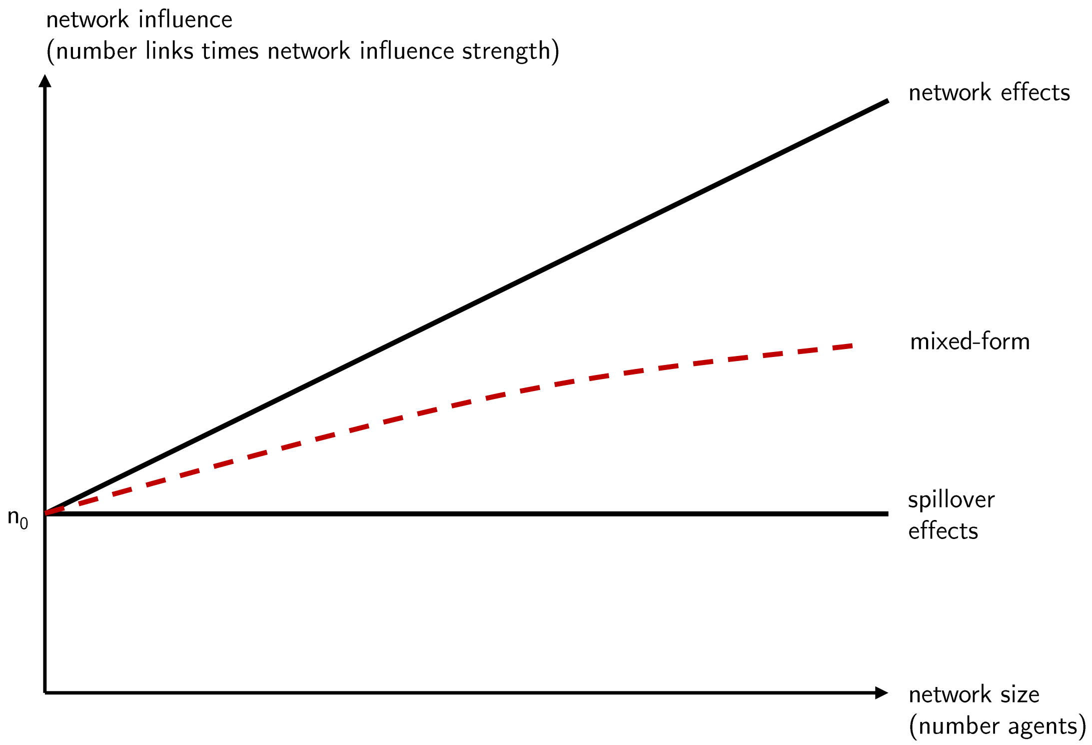

Figure 36. *Combining network effects and spillover effects*

Recasting my approach could aim to explain why links themselves form as a function of the agent's attributes and the agent's embeddedness in the network, as if airlines in the same geographical region have incentives to form codeshare linkages. Consider in this connection the series of plots in Figure 37 that present an important extension to my approach to network formation: starting from the left in Figure 37a, I see that agents may not merely choose their positioning in the network uniformly at random or preferentially but by explicitly considering what existing agents in the network fit their natural inclinations. As shown in the figure, this could be achieved by assuming that agents balance the benefits they receive from linking to agents with high positional values, such as agent i_1, with information on which of the other agents matches the agent's tastes or preferences. For instance, agent i^* would therefore also connect to agent i_6, and further link formation processes as shown in Figure 37b would build upon this strategically chosen position. Essentially, the propensities with which these links form would thus become a function of the positional values and the matching characteristics; data on both could be gathered empirically. I believe the extension I have suggested in Figure 37 is important because it directs future research explaining why links form as a function of nodes positional values (the degree of preferentiality) and the agent's attributes; it would thus enrich the model by replacing the random component of the approach I have presented by actually observable agent characteristics.

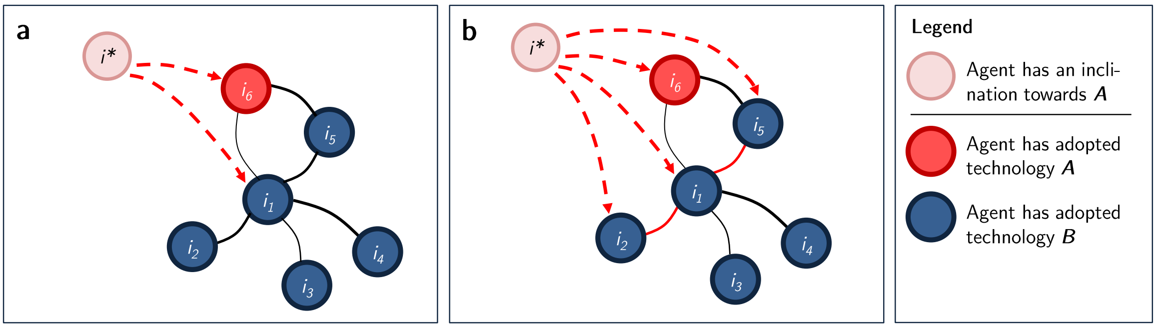

Figure 37. Extending link formation towards strategic link formation

Finally, one could harness my approach and extend the analysis from the micro level (single nodes) and macro level (global patterns) to the segment level. As shown in Figure 34, I substantiated my claim of different regimes of standardization outcomes by combining both the diversity index and network-adjusted homogeneity. By analyzing simulation outcomes using advanced clustering procedures, one could examine more directly the emergence of structural patterns in parts of a network.

5.4.5 Implications for Research on Standards and Path Dependence

My work has implications for standard diffusion research. I suspect that distinguishing network and spillover effects, as I have defined them, provides a useful reference point for theorizing different forms of network influences. My approach presents a conceptual bridge between traditional network effect theory, mostly concerned with actors being at the mercy of market forces, and network analysis, typically subject to close-knit influences among few individuals. My distinction between proportional and non-proportional growth can guide future research on distinguishing quantitatively diffusion patterns such as clustered islands of shared technologies, one standard's dominance, and multi-standard persistence.

Turning in conclusion to broader implications for path dependence theory, my work contributes to a recent stream of organizational path dependence research that concerns more accurate portrayals of how inertia builds up in organizational contexts. Path dependence theory has increasingly utilized the notion of complexity (Koch et al. 2009; Sydow et al. 2009:700; Seidel 2013). Not unlike in *NK* models (Kauffman 1993; Rivkin and Siggelkow 2002; Siggelkow and Rivkin 2006) – a class of models that theorizes inertia as a function of the system's number of elements (*N*) and the degree of connectedness (*K*) – a network's degree of interaction refers to the extent of coupling among components in a distributed system. Seminal *NK* models assume that changes are made *within* the existing configuration of a system. Change in a system is portrayed as a process where states of a fixed system flip. In contrast, I have drawn attention to the extent to which growth processes can make fundamental change in a system unlikely. In contrast to static *NK* models, the presented model assumes that the linkage structure changes as the network evolves. Existing elements gain more links as a function of their age and their embeddedness in a system. This presents an interesting extension to static *NK* models that allows to account for increasing inertia of a system over time due to increasing interdependencies.

Chapter 6

Evolving IT Infrastructures: Recycle Inc. Case

I turn to the case of Recycle Inc., a private German enterprise from the recycling sector. In particular, the Recycle Inc. case will illustrate two main pieces of my argument: that IT infrastructures are usefully analyzed as networks and that network embeddedness induces inertia. I draw on this case because I gained in-depth qualitative and quantitative insights into Recycle Inc.'s IT landscape. I conducted thirteen expert interviews that were tape-recorded, transcribed, and stored for subsequent analysis in a case study data base (refer to Table S4 for an overview of the field data). Furthermore, I gained access to a comprehensive enterprise architecture data set from the companies' central IT architecture group: data on IT support for 29 subsidiaries in 73 business activities by about 400 applications[14] was gathered in a real requirements engineering project during a three-month period in 2011 preparing a major IT transformation. The data set mainly consisted of the company's existing applications, information flows and business processes.

Drawing on my conception of IT infrastructures as networks, the first part of this chapter utilizes a design science approach (Peffers et al. 2007) to introduce a method to IT managers and architects that enables to identify and assess critical IT systems with respect to their architectural embeddedness. I demonstrate and evaluate the method's usefulness based on the Recycle Inc. case. Drawing on the growth model (chapter 4), the second part of this chapter demonstrates the model's usefulness to understand processes governing the evolution of a real IT infrastructure.

6.1 Research Context and Data

Recycling Inc. has approximately 9,000 employees and its main areas of business are waste operations, recyclables trading, services, steel and metals recycling. My point of entry was an IT unit in the waste operations business domain, employing 15 people at the time of my research. Focusing on the waste operation domain, the core waste management process was composed of the three main activities:

(i) Distributing and pricing waste operations services (e.g. different quality containers)

(ii) Operating and disposing waste including tour planning and weighting and

(iii) Invoicing, accounting and controlling services

I expected the data to reflect that process but I was surprised about the variety of different applications and their coupling. I constructed a network data set from the information I received by representing nodes as applications interacting with each other. Links materialize in implemented and actually used interfaces between two systems (Dreyfus and Iyer 2008). The network is undirected; mainly data quality issues prevented meaningful inter-

[14] Estimates were not completely precise as issues occurred in the company agreeing on a common (application) definition, e.g. how to handle multiple installations of a system and how to remove redundancies from the data set. We however tried to mitigate concerns on data quality by using a later version of the data set that has already gone through multiple rounds of reconciliation within the company.

pretation of information flow directions. Based on this specification, I cleansed the data and removed applications not interacting with any other system. I proceeded with a network of 212 applications (nodes) and 234 links (information flows). I coded the data in an n x n adjacency matrix, which I denote as Recycle Inc.'s information system (*IS*) network $\boldsymbol{B}$ (refer to data set oS2 in the online supplements). The data included three additional application attributes – technical support, ownership, and organization using the application – and three further attributes on interfaces (status, transferred data and interface type).

6.2 A Method to Assess System Embeddedness in IS Networks

Next, I develop a method to assess the importance of IT systems in organizational IT infrastructures with respect to their architectural embeddedness[15]. The method consists of a set of useful measures and visualizations to conceptualize IT infrastructures from a network perspective. To develop the method, I chose a design science approach (Peffers et al. 2007). Design science research is an important and widely accepted form of conducting research on information systems (Gregor and Hevner 2013; Hevner et al. 2004). My research followed a step-wise, iterative procedure as outlined by Peffers et al. (2007:54): problem definition, definition of scope and objectives, design and development, demonstration, evaluation, and communication. I demonstrate the method's application using a case method (Yin 2013). I introduced the method to potential target users – IT managers and architects – to evaluate the method's effectiveness. Consistent with Hevner et al. (2004) and Venable et al. (2012), I believe that case studies represent a legitimate way to evaluate design science artifacts. Based on the potential of design science research for theory building (Gregor and Hevner 2013; Kuechler and Vaishnavi 2012), I utilize the findings to discuss the underexamined theoretical link between system embeddedness and continuance inertia (refer to chapter 2.1.1).

6.2.1 Useful Measures on the Micro and Macro Level

I begin by distinguishing between three different levels of network analysis. (1.) Macro analysis focuses on patterns of interconnections. Relationship analysis (2.) is based on the types of edges and the (non-)existence of relationships. It is highly concerned with cliques, structural holes or 'boundary spanners' (Cross and Prusak 2002:9f.). Finally (3.), a micro analysis narrows the scope to the attributes of a single node (Lima 2007).

Measures on the Micro Level

When the main objective is finding and evaluating the specific nodes which are most critical with respect to some attribute such as continuance inertia, several measures on the micro level of a network (3.) serve to be useful. Consistent with Dreyfus and Iyer (2008), I expect that "[a]pplications with high positional value may be important because they influence many other applications". Following suit, I focus on metrics for the influence of applications on others. In network analysis, a variety of centrality measures are used to assess a node's influence. I focus on three of them, which are degree, betweenness, and

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[15] Earlier versions of this method have, in parts, being outlined in Fuerstenau and Rothe (2014), and Fuerstenau (2014)

Eigenvector centrality. I chose these metrics by two means. First of all, they are used most often throughout research based upon centrality in network analysis on a micro-level. Secondly, they allow for distinct interpretations. I will evaluate these metrics following the widely accepted SMART criterion for decision processes consisting of five attributes: (s)pecific, (m)easurable, (a)ttainable, (r)ealistic, (t)imely (cf. Doran, 1981; Wright, 2008). (S)pecificity concentrates on a clear target to be improved. My target is to assess the centrality of IT systems. A (m)easurable item offers quantifiable indicators. Metrics are used to define (a)ttainable goals. It needs to be as simple as possible to understand clearly their direct implications. Metrics should also clarify their reach, to be used in (r)ealistic decision processes. Finally, the (t)ime between data collection and decision need to be minimized. All centrality measures use the same source of network data. Hence, across them (m)easurability and (t)imely data collection do not differ. Both attributes are therefore not used to evaluate the usability of the metrics. They are essential for our further analysis nonetheless. Therefore, I will focus on them in the next chapter, which is concerned with the procedural model. **Degree centrality** defines (actor) centrality on a micro level most simply (Wasserman and Faust 1994). In a non-directional network, degree centrality C_D is defined in Equation 6.1 as

$$C'_D(n_i) = \frac{\Sigma_j x_{ij}}{g\text{-}1} \tag{6.1}$$

where $\Sigma_j x_{ij}$ is the sum of ties (x) between one node i and any other node j within the network, standardized by the size of the remaining network (g - 1). It focuses on the direct neighbors of a node. Hence, although the metric is easy to interpret we can only vaguely assess the influence of such a node on the overall network. An IT system with a degree centrality of zero shares no data with any other application. A high degree of centrality may indicate that the application is integrated into a dense cluster of systems which is strongly interconnected. Nevertheless, it may also hint to a system having a boundary spanning role between different systems in the IS architecture. Degree centrality is very comprehensible, as it only counts the amount of used interfaces. (A)ttainable and (r)ealistic decisions could be made on this indicator. For our purpose – to find central applications within an IS architecture – it leaves room for ambiguous interpretations as it only accounts for direct neighbors. Hence, it lacks (s)pecificity.

Another frequently discussed metric is **betweenness centrality**. It is a path-based centrality measure and particularly accounts for indirect ties between nodes (Freeman 1977; Wasserman and Faust 1994). Betweenness centrality measures the probability that a node (i) lies on a shortest path between two other nodes (j and k). We add up the probabilities for every constellation within the network. Betweenness centrality is mostly discussed when it comes to boundary spanning. Nodes with a high betweenness centrality are likely to be the only link between cliques and clusters in a network. Their importance is driven by the fact that if they are removed, the whole network may fall apart. As shown in Equation 6.2, I also standardize betweenness for the overall network (g) as follows:

$$C'_B(n'_i) = \frac{\Sigma_{j<k}\, g_{jk(n_i)}/g_{jk}}{(g-1)(g-2)/2} \tag{6.2}$$

With regards to a visualization of an IS architecture, betweenness centrality may be a good indicator for indirect dependence of applications. I take it as a point of departure for (a)ttainable and (r)ealistic decision making. One may begin asking the right questions: does an ERP *A* rely on an application *C* to get data from *B*? If so, application *C* becomes a "boundary spanner" or "gatekeeper" (Wasserman and Faust 1994). While the answers to such questions may be very insightful, the metric itself lacks an important attribute, which degree centrality already contributed for. It only partly accounts for the effects of direct links. Even with a low betweenness centrality, the application concerned may have many links to other systems, which by themselves may be interconnected. Moreover, little certainty exists that data streams between applications always take the shortest path, which is a key assumption underlying betweeness centrality.

Finally, I discuss **Eigenvector centrality,** frequently used to capture the power of a node within a network (Bonacich 1987). It is also similar to the PageRank used by Google to assess the importance of web pages within the World Wide Web. Eigenvector centrality combines attributes of the two before mentioned approaches (cf. Bonacich 2007). It does not only take the direct ties of a node into consideration but also the neighborhood of these ties. Moreover, the centrality of a node rises with the centrality of its direct neighbors. The recursive function – referring to Newman (2008) – in standardized form is given by Equation 6.3:

$$C_\lambda(i)=\frac{1}{\lambda}\sum_j x_{ij}\, c_\lambda(j) \tag{6.3}$$

It uses the adjacency matrix *B*, in which $x_{ij} = 1$, if node *i* and *j* are tied to each other. The eigenvalue λ is a constant. Transferred to information systems, one may assume that an application *i*, sharing data with a very central ERP *j,* is also more central in the overall IS architecture. The measure takes direct and indirect connections into account. Therefore, it fulfills our (s)pecific need to find central actors within a network. Due to its recursive definition, the causes of its centrality remain unclear compared to the other metrics. Thus, it is rather difficult to define (a)ttainable and (r)ealistic decisions based upon this metric. In my following analysis, I will therefore use degree centrality and betweenness centrality to assess the importance of an IT system within the IS architecture. I find both measures simple enough to derive direct decisions as well as comprehensive enough to complement each other.

Measures on the Macro Level

I turn to measures on the macro level that will be useful in understanding network formation and overall patterns of interactions in IS architectures. Macro level patterns are often visualized graphically or by adjacency matrices (Lerner 2010:355-364). I briefly introduce the following summary statistics that characterize a network's macro state: density, average degree, average clustering coefficient, average path length, assortativity, degree distribution, and giant component size. Thereafter, I sort out suitable measures for my approach to understand the evolution of IT infrastructures.

One of the most prominent coefficients for macro analysis is the **density** of a network. It can be determined by the strength and quantity of connections between dyads and triads of interconnected nodes. In an absolutely dense network every node shares a tie with every other (Borgatti and Everett 1997:253). Technically, density is the average degree divided by $n - 1$, where n is the number of nodes.

The **average degree** is the average number of links for all nodes divided by the overall number of nodes. Density and average degree characterize a network's overall degree of interconnection. If a network has a low density then typically it consists only of small components, but if the density is high enough then a single large component forms, usually accompanied by many separate small ones (Newman 2011).

The **average clustering coefficient** tapes into the extent to which triads – in social networks constellations where friends befriend with friends – are present (Jackson 2008b). It is defined as the mean over all local clustering coefficients; and the local clustering coefficient designates the number of pairs of neighbors of node i connected with each other divided by the overall number of pairs of i (Watts and Strogatz 1998).

The **average path length** is a measure of the distance – the length of (number of links in) the shortest path (or geodesic) between nodes in a network (Jackson 2008:32). As many networks are not fully connected, one typically reports the average path length within the giant component – the largest number of connected nodes.

Assortativity characterizes a situation in which high-degree nodes tend to link with other high-degree nodes (Jackson 2008:65-66). Assortativity designates a correlation in degrees (Newman 2002); it may help to shed light on the patterns of diffusion – how information flows through a network and how it is transmitted in the network. For example, a study on trade relationships by Jackson (2008:67) found a negative correlation in degrees of countries trading with each other, which was caused by a pattern where small countries tend to trade with few large countries forming a hub-and-spoke structure.

One may think of the **degree distribution** by constructing a vector of all the nodes' degrees. That is, the number of link neighbors each node holds. Based on this vector, the degree distribution is a histogram of the relative frequency with which each value of degree is present in the vector. Important patterns of scaling have been characterized by degree distributions (cf. Barabasi and Albert 1999). Typically the logarithm of degrees and relative frequencies is used to plot the degree distributions. Preferential attachment networks will be approximated well by a straight line with a negative slope (Jackson 2008:59-65). Growing random networks, in contrast, are better fit by a polynomial regression line, also with a negative slope (Jackson 2008:135).

Finally, the **giant component size** is the maximum number of connected nodes in a network.

To this point, I introduced several measures to characterize a network's macro state. Consistent with Liu et al. (2011b), I expect that it will be useful to focus on degree distributions to fit data from the IS network as this will reproduce important structural properties of the network. As focusing on degree distributions alone could result in missing important aspects of a network's structure, I believe that it is important to extend the analysis by four other coefficients.

Firstly, the clustering coefficient shows whether a node's neighbors tend to be connected. Connectedness among neighbors – which is discussed as "triads" in the sociological literature – is not reflected by degree distributions. In a network of information systems, a high clustering coefficient could indicate deadlock situations whereby information flows through various systems that tie back to the source of information. For concreteness, think of a fare engine quoting a GDS for fares before transferring optimization results to the airline's inventory, which in turn publishes the bookings to the GDS, creating an interlocked triad. Secondly, average path lengths allow estimating the distance between different nodes in a network. This is useful when differentiating between, for instance, *tree*-like and *ring*-like structures, which may have similar degree distributions but differ strongly in how fast (by how many steps) nodes can be reached from any other node (cf. Jackson 2008:32). I also harness density and giant component size as they describe to what extent the network is connected or whether a fraction of the network is unreachable, which is important for spillover and risk analysis.

The design artifact consists of the presented measures as well as a procedural model on how to apply the method. For the procedural model refer to Fuerstenau and Rothe (2014:6-7).

6.2.2 Results: System Embeddedness in Recycle Inc.'s IS Network

Figure 38 depicts Recycle Inc.'s application landscape as a network. In the figure, nodes denote applications and links denote flows of information. One may think of a node as a SAP finance module. Colors designate which business unit, subsidiary, or IT unit owns the application. Headquarter-owned ones are for instance bluish. Table 1 summarizes the macro structure of the network. As can be seen from the figure, the network is sparse with one giant component (density is 0.010). The giant component consisted of 178 nodes; average clustering coefficient is thus reported for the giant component: clustering is 0.241, indicating a low to medium connectedness among triads of nodes.

Comparing the data to a random network, my results suggest that the observed network is not a purely random network. In a network with 212 nodes, I found an average degree of 2.179. Following Jackson (2008:59), a purely random network with this average degree would have a probability of any given link forming of 2.179 divided by 212, or roughly 0.0102783. The clustering I observed in the actual network was 0.241, which is approximately 23.4 times higher than what we would see in a random network with the same size and connectivity. I hence conclude that the examined information system network is a non-random network.

Table 17. Summary statistics on Recycle Inc.'s IS network

Number nodes	Giant component	Number links	Density	Average degree	Clustering coefficient	Average path length	Assortativity
212	178	234	0.010	2.179	0.241	4.357	-0.010

While the network is non-random, it is neither planned in a central fashion. The network plot in Figure 38 shows that several of the hubs are assigned to specific regions or subsidiaries of the company. This lets me conclude that the historical, although not necessarily the actual, organizational structure determines (and certainly is determined by) the current IS network. Take for instance MEMO – an ERP/logistics system – as depicted in Figure 40d. The reddish color of the application in Figure 38a shows that the system is mostly used in the southern regions of the company, which is due to the fact that the system just entered Recycle Inc.'s IS architecture when the company acquired subsidiaries from a competitor in this region. This example illustrates how historical contingencies shape the actual clustering of an information system network.

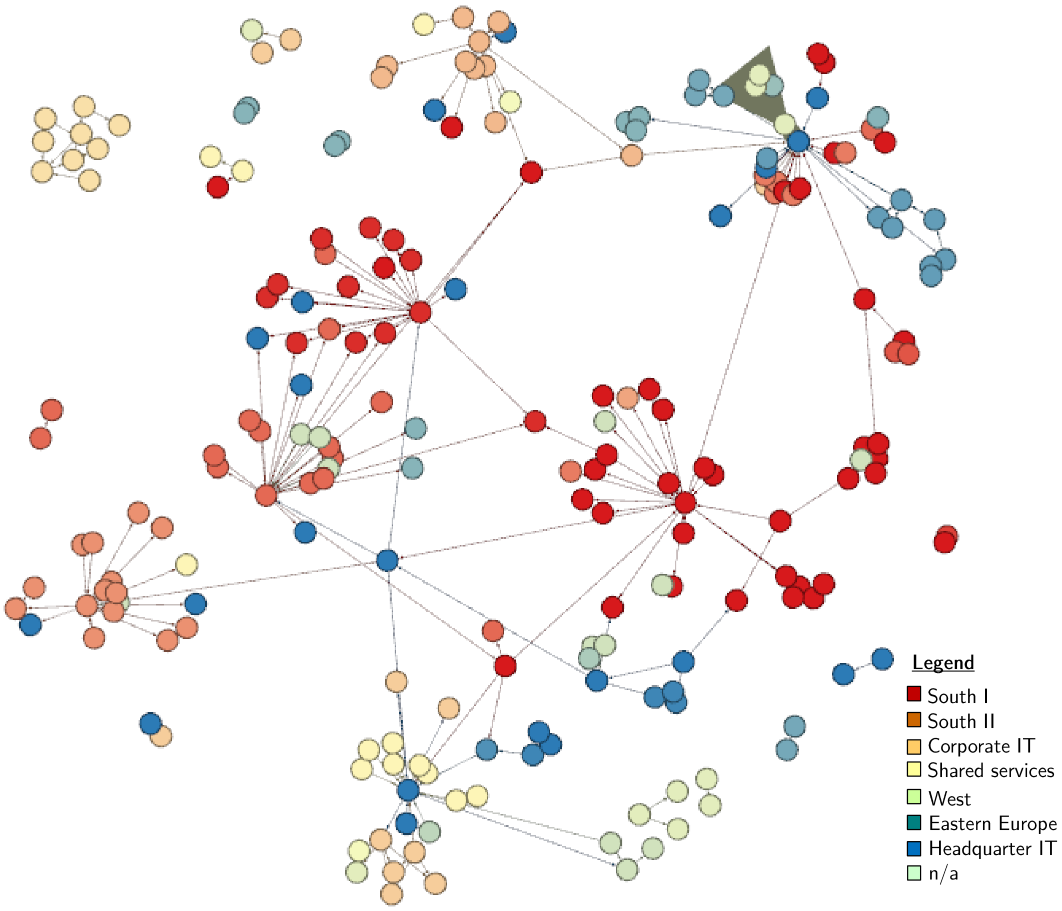

Figure 38. *Overview of Recycle Inc.'s network of information systems*

This figure shows the IT landscape of Recycle Inc.'s waste operations domain (2011). Nodes are applications, e.g. an SAP finance/controlling system, and links indicate flows of information that materialize in technical interfaces. The colors designate the responsible unit as shown in the legend, e.g. bluish systems are owned by the headquarter IT unit.

I now turn to the network's degree distribution (for raw data refer to Table S10 in the appendix). Figure 39a plots the frequency of occurrences for each number of interfaces, which I denote as the applications' degrees. The plot is a valuable initial vantage point as it already indicates an imbalance between a large number of low-degree and high-degree applications while the middle section of the plot is infrequently populated. Many applications have one or two interfaces while only few applications can be found in the middle region. From eyeballing the data, we see a "power law" structure that is typical for preferential attachment networks (Jackson 2008b). The log-log plot in Figure 39b reinforced my view and points to a robust linear relationship between the logged degree and the logged relative frequency of occurrences. Viewed together, Figure 38 and Figure 39 suggest that Recycle Inc.'s IS network tends towards a hub-and-spoke structure: a few important applications ("hubs") are surrounded by several small components ("spokes").

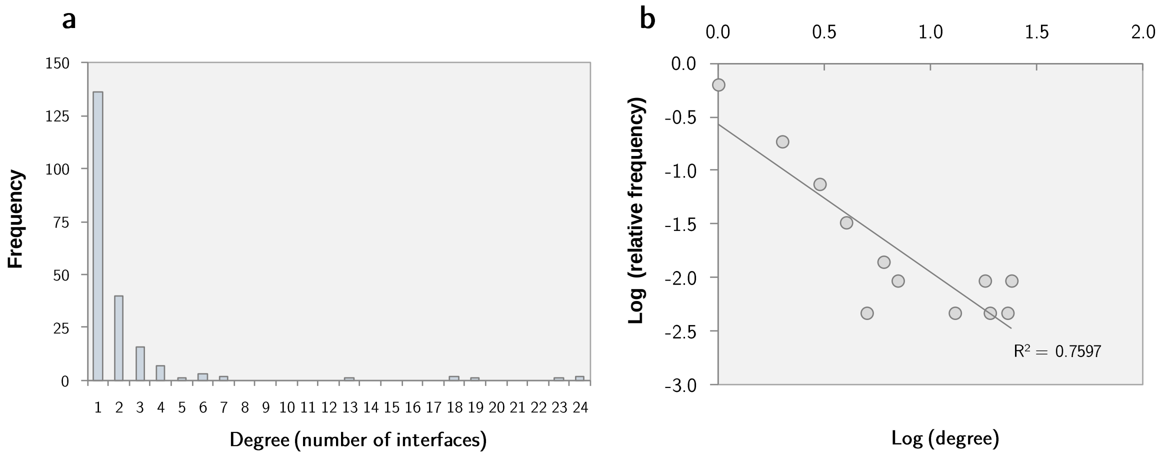

Figure 39. Degree distribution of IS network: (a) absolute and (b) log-log plot

Consistent with this finding, I focused further analytical attention on central systems with respect to their degree. Consider the left side of Figure 40 depicting degree centralities. Central systems are colored in blue, red and orange; less central applications appear turquoise and green. Figure 40a lists the most central applications: SAP Finance, MEMO, Entrance, Recyclix and Candy, of which Recyclix – the unit of analysis for my qualitative study – SAP Finance – used for invoicing and accounting applications – and MEMO are most important for my further analysis.

Various systems in Recycle Inc.'s IS architecture have been around for twenty years or longer. Recyclix (cf. Figure 40b) – an ERP/logistics application – for instance went live in 1995 after an initial planning phase (refer to archival data oS55). It replaced two other transactional systems, which are, however, still in operation. Since then, it was extended by various add-ons and extensions. A yearly budgeting and release planning process – as well as multiple uncoordinated changes – brought in various new applications, e.g. for tour planning, winter services and public waste operations (refer to interviews oS43 to oS48, and oS50 to oS52). These new programs and extensions became necessary to respond to changes in legal and market conditions as well as to react to strategic necessities. Traces of legacy clearly shape Recycle Inc.'s current IT landscape. Several interviewees (refer to interview oS42, oS44, oS48, oS49, and oS51) confirmed my impression that the IS architecture is fragmented. Consider for instance the spokes around Recyclix in Figure 40b: there are multiple interfaces to weighting applications, tools for dangerous goods reporting, as well as other controlling and reporting applications, some of which were planned while others were reactions to shortcomings of the system's current functionalities.

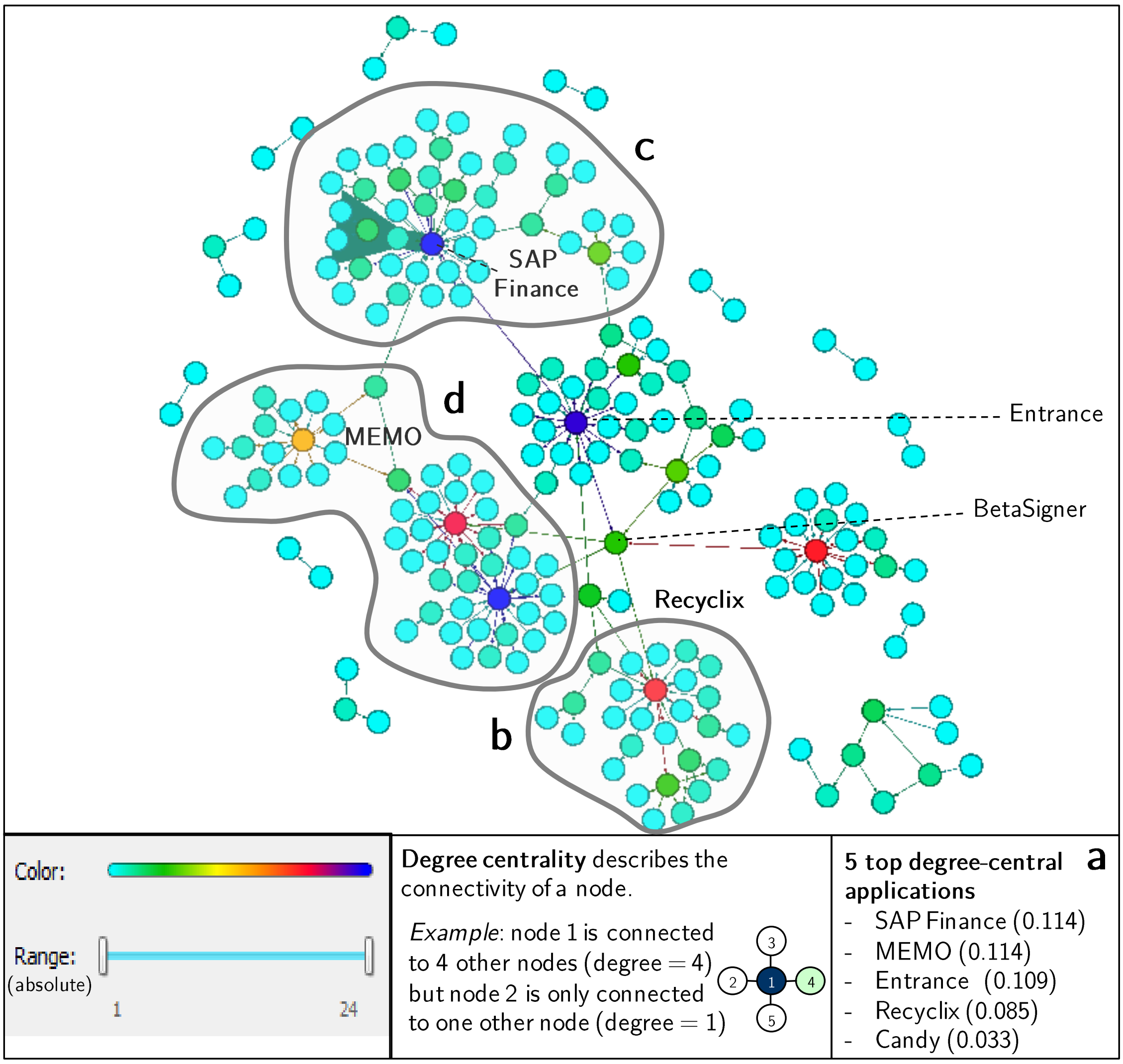

Figure 40. Degree centrality in Recycle Inc.'s network of information systems

SAP Finance, depicted in Figure 40c, is the most central system by the total number of interfaces (24 interfaces absolute). Consider the waste operations process: SAP is used mainly for invoicing and accounting. Numerous transactional systems provide data for SAP, e.g. several ERP/logistics systems, weighting and tour planning programs; this makes the system an important hub. Furthermore, many applications use data from SAP, e.g. a controlling cockpit, a data warehouse and several archival systems. The system's high degree approximates well the perception that emerged in my interviews (refer esp. to interview oS41): the system is strongly embedded in Recycle Inc.'s organizational activity. Interviewees reported that Recycle Inc. had not updated SAP from R/3 for a long time (refer to interview oS41 and oS44); this exemplifies the company's inertia arising from business-critical yet strongly embedded (and customized) systems.

Moreover, when an IT system is characterized by high betweenness centrality, IT management should be alert: the overall IS architecture is at risk of break down if the IT system fails to provide its services. The example of BetaSigner (refer to Figure 41f) indicates that such systems are often important gateways.

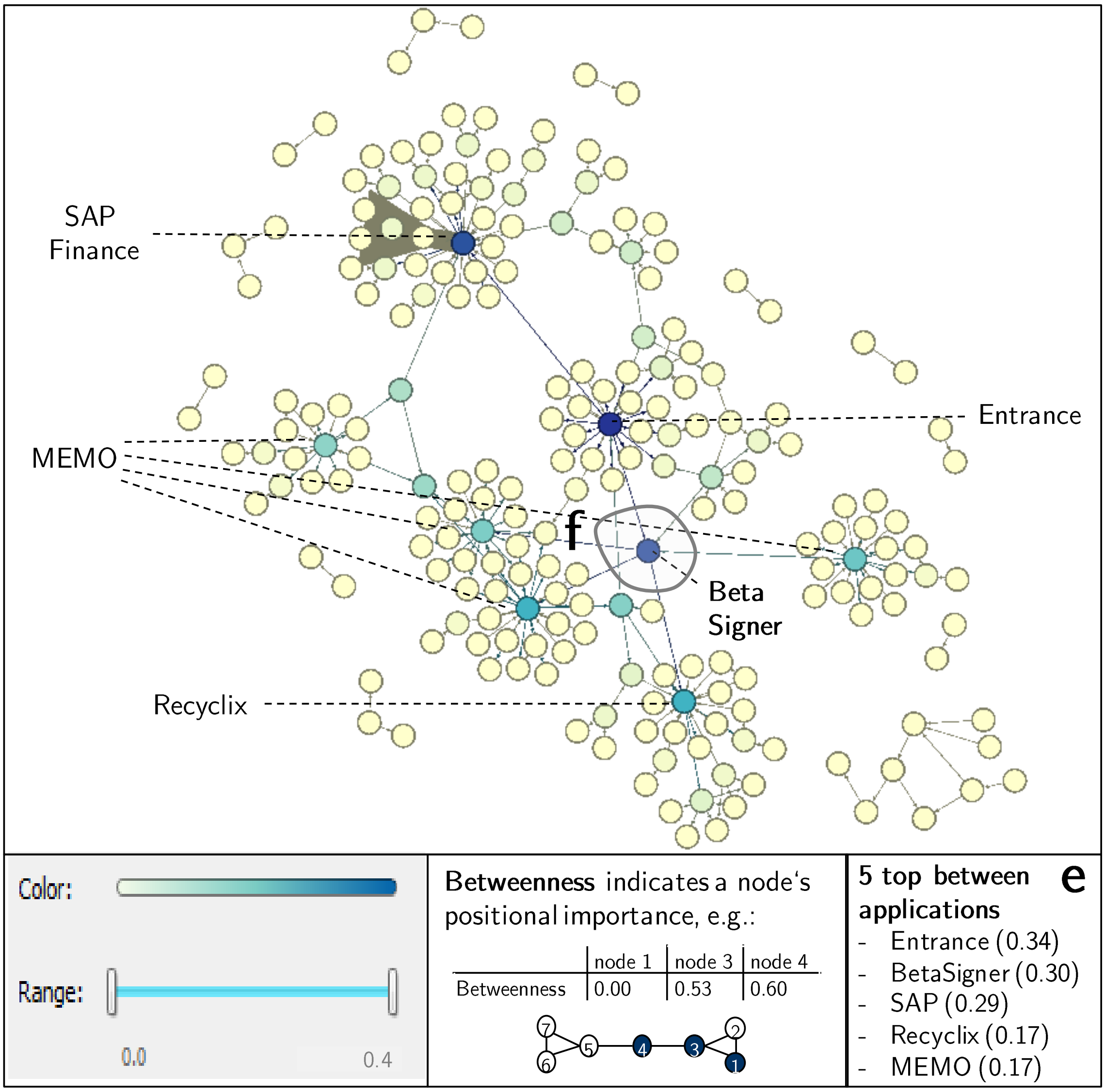

Figure 41. Betweeness centrality in Recycle Inc.'s network of information systems

Assortativity denotes that high-degree nodes tend to connect to other high-degree nodes. Recyclix for instance interfaces with other important hubs in the application landscape, e.g. SAP (cf. Figure 40c) to automate invoicing, accounting and dunning. Newman (2002) claims that technological networks often show a negative assortativity (cf. Jackson 2008:66). I did not observe assortative mixing in the data (assortativity degree: -0.0096). A possible explanation for this lack of correlation among high-degree nodes is the specific process by which IS networks form: I expect that low-degree nodes ("small programs") attach to a few (or one) high-degree nodes. These high-degree nodes in turn connect to a large number of low-degree nodes as well as other high-degree nodes. These dynamics tend to outweigh the degree of correlation among high-degree nodes. The network representation (cf. Figure 38) also points in this direction of "islands of shared technology": five to six high-degree hubs, e.g. SAP Finance and Recyclix, are complemented by many spokes. The IS network at hand is characterized by a hub-and-spoke network.

Hub-and-spoke structures intuitively suggest a preferential growth process in which new nodes attach preferentially to high-degree nodes. In the following sections, simulation results are presented to suggest a network formation process that fits with the empirical data; it is intended to add our understanding of generative mechanisms constituting real information system networks: *How did this network form? To what extent is it random or preferential?*

6.2.3 Discussion: Linking System Embeddedness and Continuance Inertia

Furneaux and Wade (2011) link system embeddedness and continuance inertia. I suggested a method to assess the extent of system embeddedness using measures from network analysis. I identified most central systems in Recycle Inc.'s IS architecture with respect to degree and betweeness centrality. I found that degree is a straightforward measure that can easily be applied and communicated to stakeholders; a high degree points to important systems being surrounded by a large ecosystem of satellites. I referred to the examples of SAP Finance (refer to Figure 40c) and MEMO (refer to Figure 40d) to illuminate why a high degree is often associated with continuance inertia. In addition, betweeness centrality highlights systems spanning different parts of the landscape. Viewed together, I conclude that both measures complement each other in assessing the degree of system embeddedness. In case of a high degree centrality, a large number of other systems depend directly on an IT system; if the organization's ability to maintain the system drains or the support is discontinued, organizational measures to replace the system may be drawn back; it is easy to imagine situations in which systems embed so strongly in the organization that serious inertia to discontinue the system arises (e.g. because of difficulties in transferring interfaces or business logics inscribed in the system). I believe these results are a theoretical step forward towards a better understanding of how system embeddedness affects continuance inertia.

In Table S12 in the appendix, I have outlined a theoretical model that could be used in future research to test the relationship between system embeddedness and continuance inertia. I believe this model is important as it links system embeddedness and continuance inertia in a way that one can operationalize by drawing on available, quantitative data from a company's IT documentation. My contribution over Furneaux and Wade (2011) is that the network measures – on which my approach builds upon – can replace, or at least complement, the potentially biased expert judgments used in previous works.

6.2.4 Concluding Remarks

This study explored what network analysis concepts are helpful in assessing IT infrastructures with respect to system embeddedness. I also aimed at shedding light on the reasons why system embeddedness affects continuance inertia. I suggested a method that models system embeddedness as the positional value of an application in a network of applications and interfaces. To identify embedded systems, I suggested centrality measures from network analysis. I found that degree centrality is a simple and yet powerful measure that captures the number of neighbors of a system. When a system shows a high degree, it is likely to exhibit high levels of inertia as illustrated in the example of SAP Finance (refer to Figure 40c): Organizations may delay suspensions or updates as a large number of interfaces need to be adapted, some of which may be undocumented or idiosyncratic. Changes would ripple and require the adaptation of several other business-critical systems. Additionally, betweeness centrality captures a system's position as a boundary spanner. Systems with high betweeness centrality will also be critical with respect to continuance decisions as shown in the example of BetaSigner (Figure 41f): they connect different clusters of an IT infrastructure. In case of their discontinuance the architecture is at risk of breaking down, so they may stay operational despite capability shortcomings.

My work is not without limitations. Firstly, I focused on the technical integration between information systems as one important dimension of embeddedness (refer to Furneaux and Wade 2011). Further work is necessary to operationalize the embeddedness of systems in organizational work practices. A possible starting point is work by Aier and Winter (2009) on business and IT architecture linkages. Secondly, although I could observe legacy traces in the data, I could not track historical growth processes over time directly. Recasting my approach to consider network dynamics would be a natural next step. This could be done by gathering further network data at different points in time. My vantage point in the next section is a simulation that fits the network dynamics with empirical data; it aims to improve our understanding of generative mechanisms constituting real information system networks.

Turning in conclusion to managerial implications, I believe that IT managers can benefit from concentrating on *central* systems in their transformation efforts. Information systems having reached a critical size and risk status will be more likely to exhibit continuance inertia. Systems playing a central role in a company's IT infrastructure are also more likely to be essential in multiple business processes. In this connection, my approach provides IT managers with a standardized procedure to assess system embeddedness and continuance inertia. A dashboard solution could build up on my approach.

6.3 Insights from Agent-based Simulations: Architecture Evolution

6.3.1 Model Operationalization

In chapter 4.2, I suggested a hybrid random growth model with the following main parameters (cf. Figure 17): *proportionality (p), degree of interaction (m) and degree of preferentiality (α).* In the model, where new nodes enter every turn, links form in random, preferential, or hybrid ways.

For the purpose of this study, I constructed a compact version of the model focusing on fitting the growth process of the information system network at hand. Firstly, I excluded strategic agents from the model – hence, new node's entering a network select partners purely at random or preferentially (or in a hybrid way). I also excluded proportional (relative) growth from the model as experiments suggested that a non-proportional (absolute) growth process would approximate the data better. Thirdly, I extended the model by bringing in two additional parameters describing the growth logic of a network in more detail: the *variance of interactions* (σ_m) and the *dropout rate* (τ).

The *variance of interactions* (σ_m) portrays the extent to which a new node's *number of interaction partners* (m) varies with *m*. In the basic model a new node links to *m* partners. This produces degree distributions mismatching empirical distributions: as *m* is a lower bound to a node's degree (as the network is undirected), each node has at least a degree of *m*. In the extended model, I therefore assume that *m* is distributed randomly normal[16] with σ_m. I did that, because it appears plausible from studying empirical degree distributions that the *law of large numbers* applies for links forming in information system contexts.

I furthermore extended the model by a process where existing nodes *drop out* of the network. I model a simple dropout process as shown in Algorithm A.7: Each period, I select a certain fraction of nodes uniformly at random that will drop out in the next period. The user inputs a *dropout-rate*, which is the fraction of the given population of nodes that is in danger of fall out of the network (initially all nodes are not *endangered*). Then, in each period a fraction of nodes is flagged as endangered (line 5-8). In the next period, endangered nodes and their links die (line 1-4). This results in a simple dropout process where the absolute number of endangered nodes increases relative with the network size.

While growth processes may reinforce a standard if new nodes attach to previous ones and positive externalities or spillovers are present, dropout may lead to segregation, decay, or generally counteracting dynamics. It is easy to imagine the empirical process: existing information systems will be dispended or replaced at the end of their lifecycle (cf. Furneaux and Wade 2011). I define a mortality rate (τ). τ scales between zero and one; each period, a fraction of τ nodes is picked uniformly at random and removed in the next period from the population of nodes[17]. All existing links will also be removed from the network. I bring in dropout as simulated networks will tend to overestimate the size of the giant component. In a (random) network where λ (the link probability) is larger than $log(n) \ / \ n$, the probability that the network is connected will always tend to one (cf. Erdös and Rényi 1961; Jackson 2008b:92-97). Hence, the network will remain connected as new nodes in the model only attach to existing nodes in the giant component. A dropout process restricts the giant component's size as the network can now decay.

Algorithm A.7 Dropout

```
1:  foreach node with 'endangered' do                        > flagged nodes die
2:    foreach link do die end foreach                        > first all links die
3:    die                                                    > then the node dies
4:  end foreach
5:  foreach node do
6:    let rd := random-float 1
7:    if rd < dropout-rate then endangered := true end if    > node is flagged
8:  end foreach
```

Viewed together, Table 18 summarizes the main parameters of the given model. The next section presents results from fitting selected models to the empirical data.

[16] Note that in cases where $\sigma_m = 0$, the model is equivalent to our base model. When the degree of interaction after the transformation is smaller than one, the model sets it to $m = 1$. For small *m*, i.e. when $m = 1$, this produces a distribution that cuts off the lower part of the "Gaussian" curve.

[17] In an empirical study, Aier et al. (2009) estimated "probabilities of death" for applications based on enterprise architecture data in three companies. The values ranged considerably between years and companies from 0.00 to 0.41 (company A), 0.05 to 0.19 (company B) and 0.00 to 0.18 (company C).

Table 18. Main parameters of the simulation model

	Simulation parameter	Math. notation	Description
Initialization	Start-network	-	Initialize a static network with a given *network type* (random, preferential)
	No-init-nodes	n_0	The initial network consists of n_0 nodes
	Link-probability	λ	Nodes become linked by a certain *link probability* (λ), which is only applicable for random networks.
Growth	Degree-of-interaction	m	Each "new" node finds partners given a certain *degree of interaction,* which is the number of links formed
	alpha	α	The *degree of preferentiality* (α) indicates whether a new node attaches primarily to high-degree nodes ($\alpha = 0$) or to random nodes (α = one)
	variance-of-interactions	σ_m	The extent to which a new node's number of interaction partners varies
	Dropout rate	τ	If the *dropout rate* (τ) is non-zero, pick τ * n nodes at random and tag them as "endangered". Endangered nodes and their links are removed in the next period.

6.3.2 Model Implementation and Experimental Setup

The model was coded in Netlogo 5.0.3 as a branch of the *network growth model.* The program code of the *compact network growth model* is attached in code example oS4.

I use a simulation approach to derive parameter values of the model as the number of parameters complicated a mean-field approximation. Table 19 illustrates the precise steps carried out at the simulation's beginning and at every step until the time limit is reached.

Table 19. Simulation procedure

Step	Action
I	Initialize a static network with a given *network type* (random, preferential) consisting of a certain number of nodes (n_0) linked by a certain *link probability* (λ)
II	Grow the network until the time limit is reached
a*	Create one new node and set status to 'new'
b*	For each 'new' node, find partners given a certain *degree of interaction* (m), *a variance of interactions* (σ_m) and a degree of preferentiality (α)
c*	If the *dropout rate* (τ) is non-zero, pick τ * n nodes uniformly at random and flag them as 'endangered'. Endangered nodes and all their links are removed from the network in the next period
d*	(Re-)calculate measures of the network's macro state, i.e. number nodes, links, density, average degree, clustering coefficient, average path length and assortativity
* These tasks are repeated each period of the simulation	

6.3.3 Result: Enriched Preferential Attachment Fits the IS Network's Growth

Based on the procedure described in Jackson (2008:139), I calculated m (the degree of interaction) for the simulation model directly. Since m is the number of links that form each period, it is half of the estimated degree in each period (as I used an undirected model). The overall degree is $2tm$, and so m is half of the average degree. In the network, average degree is 2.179, and so m is roughly 1. I restrict further analysis to $m \leq 2$.

I then estimated values for α - the degree of preferentiality. After qualitative analysis of several models, I ran 40 batch simulations with 100 runs per model (40 models by 100 runs equals 40.000 experiments). I restricted the time limit to 200 (or 250 runs, respectively) as the overall degree is 234, which must equal $2t$ (because I set $m \leq 2$). I did not use the precise run numbers as I had to account for dropout processes in several models.

I analyzed how well the models fitted the empirical degree distributions by the means of regression. When fitting several models to data, I concentrated on finding an appropriate regression for degree distributions and reporting the coefficient of determination (R^2). I refined these results to reach the best possible fit between data and regression. I calculated a (linear, quadratic, or cubic) regression model showing a good fit with the results of the simulation (in terms of R^2). Then, I observed the fit between the regression and the empirical data.

In addition to the degree distribution, I used additional coefficients as described in chapter 6.2.1. I acknowledge that iterative procedures could find an optimal solution automatically. Jackson (2008b:139f.), for instance, suggests that parameter values for hybrid models can be estimated by an iterative least squares regression or a maximum likelihood estimation. I did not use these approaches as I was interested in a multiplex characterization of the data including other coefficients also.

I sampled one degree distribution from the 100 runs uniformly at random and estimated an appropriate regression model – linear, quadratic or cubic – fitting the distribution of degrees for the run. I then fitted this regression model to the empirical distribution and calculated the degree of determination. Table 20 reports results for five models where m equals 1 in which I excluded variance in the degree of interaction (parameter 'variance of interaction' was set to zero). I also report three further models, which I discuss below (refer to Table S13 in the appendix for the complete range of simulated models).

All quadratic models with $m = 1$ and $\alpha \leq 0.5$ fitted the data well (cf. Table 20, R^2 ranged from 0.914 to 0.941). For regression results of one quadratic model from the simulated networks (i.e. model 9) refer to Table S11 in the appendix. As the simulation uses a preferential growth model for round ($m * \alpha$) < 1, and as I restricted m to 1, all of these models (i.e. model 9 to 17) select partners based on a preferential attachment procedure.

I then calculated the simulated models' normalized distances from the main coefficients to the empirical data. The top of Table 21 shows three models with the closest distance to the data. The bottom part of the table gives estimates for one model as a representative for all preferential attachment models. These models (e.g. model 9), however, did not fit well with respect to clustering coefficients, because for low degrees of interaction ($m = 1$)

and preferential growth, new nodes attach to a single hub without connections to other nodes.

Table 20. *Results of selected models for regression*

		Model parameters				Goodness of fit		Unstandardized coefficients		
	Model	m	Variance of *m*	α	τ	R^2 to model	R^2 to empirics	Log degree	Log degree^2	(Constant)
Preferential	Model 9	1	0	0.0	0.0000	0.959	**0.941**	-3.248	1.111	-0.045
	Model 11	1	0	0.1	0.0000	0.958	**0.925**	-2.610	0.706	-0.124
	Model 13	1	0	0.2	0.0000	0.964	**0.914**	-2.496	0.554	-0.144
	Model 15	1	0	0.3	0.0000	0.940	**0.942**	-3.192	1.123	-0.082
	Model 17	1	0	0.4	0.0000	0.892	**0.940**	-3.795	1.692	-0.009
Hybrid	Model 36	1	2	0.7	0.0000	0.947	**0.705**	0.543	-1.686	-0.659
	Model 31	1	1	0.7	0.0000	0.899	**0.781**	-0.573	-1.144	-0.387
	Model 37	1	2	0.7	0.0001	0.947	**0.724**	0.301	-1.589	-0.572

By incorporating variance in the degree of interactions – as shown for model 36, model 31 and model 37 in Table 21 – I could decrease the distance between the model and the empirical data considerably. Model 36 for instance echoed the empirical data very well with respect to clustering coefficient and average path length. Model 31 performed even better with respect to network density. These models, however, showed relatively poor performance with respect to fitting degree distributions as shown in Table 20.

Table 21. *Results of selected models for main coefficients*

Model	m	σ(m)	α	τ	Density	Clustering coefficient	Path Length	Distance[2] (normalized)
Empirical data	n/a	n/a	n/a	n/a	0.01000	0.241	4.357	n/a
Model 36[1]	1	2	0.7	0.0000	0.01399	0.252	4.688	0.167
Model 31[1]	1	1	0.7	0.0000	0.01084	0.286	5.959	0.177
Model 37[1]	1	2	0.7	0.0001	0.01412	0.252	4.980	0.193
Model 9[1,2,3]	1	0	0.0	0.0000	0.00981	0.001	5.199	1.028

[1] Average results for 100 simulation runs; time limit was set to 200 ticks
[2] Mean squared differences of model and data in normalized density, clustering coefficient and path length
[3] Results without significant differences were obtained for model 11, 13, 15 and 17

By incorporating dropout, I could significantly enhance the fit of the model with respect to the size of the giant component (cf. Table 22).

Table 22. Size of the giant component for different dropout rates

Model	Number of nodes	Number of links**	Nodes in giant component	Fraction of nodes in giant component
Empirical data	212	234	178	0.840
τ = 0.000[1]	212	234	212	1.000
τ = 0.001[1]	186.08	168.87	134.78	0.724
τ = 0.002[1]	167.88	137.85	91.02	0.542
τ = 0.003[1]	154.05	118.34	68.51	0.445

[1] Average results for 100 simulation runs; time limit was set to 200 ticks
[2] Results are reported for preferential attachment model with α = 0.0 and m = 1

6.3.4 Concluding Remarks

This study aimed to describe important generative processes of IT infrastructure evolution. I used a simulation approach to breed information system networks in a virtual laboratory. Based on network characteristics and estimates of clustering for a real information system network, I showed that information system networks are non-random networks. I utilized a model of network formation that fitted degree distributions and other important structural coefficients to empirical data. I found that preferential attachment – as a special case of a hybrid model for low degrees of interaction – was the best proxy for the network's degree distribution (cf. Table 20). Preferential attachment, however, performed poorly in fitting the data's clustering coefficient (cf. Table 21). This was due to the fact that, for low degrees of interaction new nodes attach to a single hub only, and peripheral nodes remained unconnected among each other. To improve the fit, I brought in variance in the degree of interaction (cf. Table 21) and a dropout process (cf. Table 22), which enabled me to approximate clustering coefficients, giant component size and path lengths more closely.

I conclude that the evolution of the information system network at hand is characterized well by a dropout-enriched preferential attachment with variances in link formation.

The degree distribution was best approximated by a quadratic regression with a positive slope on the log-log plot in the range for log(degree) > 1.0 (refer to Table S11 in the appendix). Other researchers used mostly linear models to approximate preferential attachment processes (Jackson 2008b:63f.). I believe that the regression model provides a better fit for the data as the company acquired a number of subsidiaries from a competitor in the years after 2008. Integrating these applications into the IT landscape altered the network structure and introduced several high-degree nodes. Refer to MEMO as depicted in Figure 40d. These applications had not been integrated into a single business solution at the time of my research, which potentially skews the data towards more high-degree nodes. Integrating them would remove several high-degree nodes from the plot and could hence lead to a straighter line.

Before sketching future directions and managerial implications, I emphasize two conditions that limit the generality of my approach. First, while a preferential growth model – that suggests an exponential increase in degrees for critical applications – fit historical data well, I have little evidence that this growth logic holds when predicting future growth. My interviews – refer especially to expert statements in oS42, oS43, and oS49 – partly mitigated concerns about the predictive power of the model as stakeholders described equivalent dynamics across different contexts and times. However, construing boundary conditions across space and time will increase the model's usefulness.

Furthermore, company efforts to consolidate the IS architecture, centralize redundant applications, or integrate interfaces in service-oriented ways could balance or even counteract increasing inertia from growing numbers of interfaces and IT systems. One may thus collect further data on cases in which (several) transformations have been performed in the past to see how major shocks affect structure and diversity in an IS network.

I see three particularly promising ways to proceed further. Firstly, I used a simulation to create a model portraying the IT architecture's historical growth process. A natural next step would be to construe predictive models that describe how an IT landscape is expected to develop in the future. I believe this is important – also from a practical point of view – when deciding on the right time to displace or split off critical IT systems, which may otherwise grow out of control or costs.

Secondly, while I fitted the network's growth process, I did not fit technology/standard diffusion in the network. Consistent with my theoretical results, my interviews suggest homogeneity of technologies around central hubs of the network. Consider the network plot in Figure 38. We see quite clearly, for instance for the reddish applications in the Southern region, how the organizational structure is imprinted in the IS architecture. Within my interviews, I gained the impression that the clustering around hubs also correlates with technology diffusion. I believe this observation strengthens my theoretical argument from the previous chapter that technological influences spill over directly from node to node. Future research could thus aim to integrate real world data on growing IS networks with strategic agents. Strategic growth models not only answer how particular networks form but also why they form (cf. Jackson 2008b). This aims at understanding the cost and benefit structures of agents to choose actions (e.g. to adopt technologies) and to form links in more detail. In this way, one could learn in more detail how technological paths build up in clusters or segments of the network. As a starting point, one could harness the approach I have presented in chapter 4.2.3 – with ν agent types selecting one of k technologies – to see whether the model is able to match observed levels of diversity in the network. This presents interesting challenges for future research.

Finally, I have drawn attention to growth and dropout as two processes that are of particular importance to describe how IT infrastructures evolve. Using the terminology used by Palla et al. (2007) in a model to quantify social group evolution, I defined growth as a "birth" process where a new node emerges without predecessor and drop-out as a "death" process where a node disappears without successor. In addition, future work could introduce further important evolution processes. Referring to Palla et al. (2007:664), I believe it is useful taking into account

- Merges: several nodes join together (i.e. systems become integrated or consolidated)
- Splits: a node splits in several smaller nodes (i.e. modularization or service-enabling)
- Contractions: a node loses internal elements (i.e. internal complexity decreases) and
- Expansions ("growth"): a node gains internal elements (i.e. internal complexity grows)

Turning in conclusion to the broader implications for path dependence and other lines of research, I believe it is important to emphasize that central IT systems can gain importance over time in exponential ways. IT managers should consider that a critical IT system today might be drastically more critical tomorrow. Humans tend to forecast linearly. Therefore, exponential growth processes in the IT landscape may remain underappreciated. This can undermine efforts to replace, consolidate, or reengineer IT landscapes. An interesting trade-off exists between the positive effects of growth on alignment between business and IT structures and the, often hidden, side-effects. In preferential settings, add-ons and new systems attach primarily to well-tested, approved solutions (reflected by their above-average degrees). These extensions are important, because they fulfill previously unaddressed needs of the organization and are thus important drivers of business innovation. However, these results also point to a process in which inertia builds up for central IT systems in exponential ways. Central systems become more and more embedded in the company's IS architecture. This observation is important with respect to risk evaluation, strategic planning, and investment decisions. Managerial understanding of the underlying dynamics will become more and more decisive as technological advances (e.g. cloud services, service-oriented architectures, and web services) further magnify the degree of distribution in future IT infrastructures. My work also contributes to the literature on network formation. I found that hybrid models with low degrees of interactions (especially m equals one) tend to underestimate clustering in the network. Enriching a preferential or hybrid growth process by variations in interactions can produce a better fit with real world networks.

Part III

Path Breaking

Chapter 7

A New Standard in Airline Distribution IT?

In this chapter, I suggest an empirically-grounded contagion model to study path creation scenarios for a new standard in airline distribution IT. I believe contagion models are superior to traditional network effect models because they enable going beyond the network size to spillover effects among individual agents in a spatial network as an important explanatory for standard diffusion (Afuah 2013; Aral et al. 2009).

Consistent with this view, several expert interviews reinforced my impression that spillovers are important for standard adoption in airline distribution IT. Consider the following examples:

> "*Phoenix Travel*[18] *tends to follow SWISS, that's a historic thing, that's another thing you will find in the airlines, that airlines at one point or another will have, many airlines will have invested in another airline or there was a time at which they were working together when one airline was in very big trouble. And those legacy alliances remain.*" (revenue management expert; refer to interview oS17)

> "*For that, the old inventory was just not capable any more. You need inventories that allow for interlining, offer codeshare connections, you definitively need more product classes, because all the others have that; certainly it is the precondition for joining an alliance.*" (revenue management expert, refer to interview oS2)

> "*Because what happened is that also many of the leaders of the organizations come from another airline too. So there is a lot of cross fertilization in the carriers.*" (revenue management expert; refer to interview oS17)

I believe these examples illustrate the fundamental importance of spillovers for decisions about whether to adopt standards in airline distribution IT. Consistent with this view, I develop a model that takes into account influence-based contagion among individual agents as the primary driver for standard adoption. Recently, network analysis has been established as a powerful tool with which to study systematic risks in the financial industry. The IMF uses network analysis to assess potential cascades of failures from systemic linkages among banks (Minoiu and Reyes 2011). The model closest to my thinking is a contagion model by Elliott et al. (2014). It models a network of states (i.e. in the Euro zone) interacting via financial linkages and it assesses the extent to which one state's failure triggers cascades of other states' breakdowns.

An agent-based simulation approach is chosen; I followed the procedures described by Gilbert and Troitzsch (2010), kept the model simple and plain, and fed it with empirical data. I gained invaluable insights for specifying the model by interviewing revenue management experts from SWISS. I constructed a data set of codeshare linkages among more

[18] To protect privacy, the carrier's name was anonymized but it is not of particular importance for the further proceeding

than 200 airlines, which I use to test different scenarios with respect to the diffusion of the new standard. I select one (trigger) airline uniformly at random and make this airline adopt the new standard. This starts the internal loop of the algorithm, which cascades through the codeshare network assessing whether its codeshare partners will adopt and potentially switches them to the new standard if certain thresholds are exceeded. In the initial, simple threshold model – which I extent later – an agent adopts if most of its neighbors have already done so. Using these simple rules, the algorithm checks for contagion over multiple rounds until it has snowballed through the entire network or until all nodes in a connected component have been assessed. Then, the algorithm triggers a new intervention. After each intervention, I track the (cumulated) fraction of airlines having adopted the new standard.

7.1 Research Context and Data

Focusing on interactions among airlines, my starting point is the topology of codeshare linkages among airlines. Codesharing is a marketing practice in which "one airline (the *marking carrier*) marketing and selling its own itineraries and services on flights that are actually operated by a different airline (the *operating carrier*)" (Hu et al. 2013:1177). For a carrier like Lufthansa, half of its marketed flights are operated by allied carriers (Gerlach et al. 2013). Codeshares and other multicarrier revenues are a crucial factor in airlines' business strategies and account for up to 10% of the generated revenues (cf. Gerlach et al. 2013; Hu et al. 2013).

My interviews suggest that codesharing is not only a marketing practice but also important for technological choice on the operational level as inventories must be shared with and flight availabilities will become exchanged between partners (refer to interview oS7 to oS14). The basic level is the swapping of a block of seats. This ranges from the free sale of seats to the ability to sell the last seat of the other airline. To achieve this integration, a codeshare mapping is agreed between carriers, which will require at least a minimum level of standardization for inventory data exchange. This is accomplished by using booking classes as data exchange between inventories, by default, takes places on a segment/booking class level (refer to interview oS10). Exceptions include only non-standardized bid price exchanges between particular carriers.

I constructed a data set from public data on all existing airline codeshares as of January 2012. The data contained 231 commercial airlines as listed with codeshares in the GDS (data was crawled from the GDS by *airlineroute.net*). After cleansing the data for carriers that ceased operations until December 2013, I continued with a list of 213 carriers. My sample contained all top ten airlines by passenger traffic expect Ryanair. The list contained a total of 1,570 (bidirectional) pairs of partnerships on nearly 16,900* routes around the world (*duplication). After cleansing the data with respect to the abandoned carriers, I ended with a dataset of 850 (unidirectional) codeshare linkages.

I weighted linkages by the number of codeshare routes between two carriers as a proxy for the intensity of collaboration. As illustrated in Figure 42, the network was thus undirected, weighted, and non-multiplex – meaning that I considered only one type of linkages between nodes. I coded this network in the $n \ x \ n$ adjacency matrix $\boldsymbol{A}$ (refer to data set oS1 in the online supplements).

Finally, I included two node attributes to account for agent heterogeneity: alliance memberships (*i*) and size (*ii*). An airline alliance (*i*) is an "agreement between multiple independent partners to collaborate in various activities to streamline costs (e.g., by sharing sales offices, maintenance facilities, ground handling personnel, check-in and boarding staff, etc.) while expanding global reach and market penetration" (Hu et al. 2013:177). Alliance members often use codeshares intensively. Alliances are also important for technological choice as members often agree on minimum standards for operational and technical collaboration. Airlines entering an alliance must demonstrate their ability to conform to these standards. Compliance is, for instance, checked via catalogs of technical requirements before new airlines can enter. I coded whether airlines belong to Star Alliance (1), Sky Team (2), Onewold (3), or whether they do not adhere to any alliance (0). I used public data from the alliances as of October 2013 and also coded affiliated airlines as alliance members.

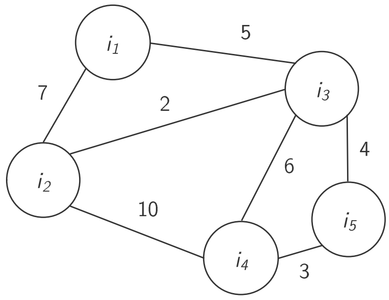

Figure 42. An undirected, weighted, and non-multiplex network

I further included firm sizes (*ii*) drawing on the number of destinations as of March 2014. I used this measure, because complementarities in the route network are an important proxy for the attractiveness of an airline. The potentials for technical and commercial collaboration among carriers will often depend on the number of destinations.

7.2 Structural Analysis of Codeshare Network

7.2.1 Macro Structure of the Network

Structural analysis – based on network visualizations and measures – of the codeshare network *N(g)* was a first step to illuminating how interactions among airlines affect standard diffusion. The codeshare matrix ($\boldsymbol{A}$) contains 44,084 zero values from a total of 45,369 cell entries. This results in a network density – which is a measure for the ratio of present to potential linkages in a network – of 0.038. Despite the network's overall sparseness, one giant component within the network appears densely connected. Figure 43 allows insight into the structure of the network and shows several macro level indicators.

We can observe a *core-periphery structure* in which "core members are densely connected to one another and peripheral members are connected to the core but not to each other" (Borgatti and Everett 2000; Valente 2012:50). We see, for instance, that a carrier in the dense core such as Lufthansa (LH) has codeshares not only with other core members (e.g. United/UA, US Airways/US, and Turkish/TK) but also links to the periphery (e.g. Air Malta, Air China/CA, and Adria/JP). In contrast, a more peripheral carrier such as Adria/JP links predominantly with core members (e.g. LH, SAS, Austrian, Aeroflot, Brussels, SWISS/LX).

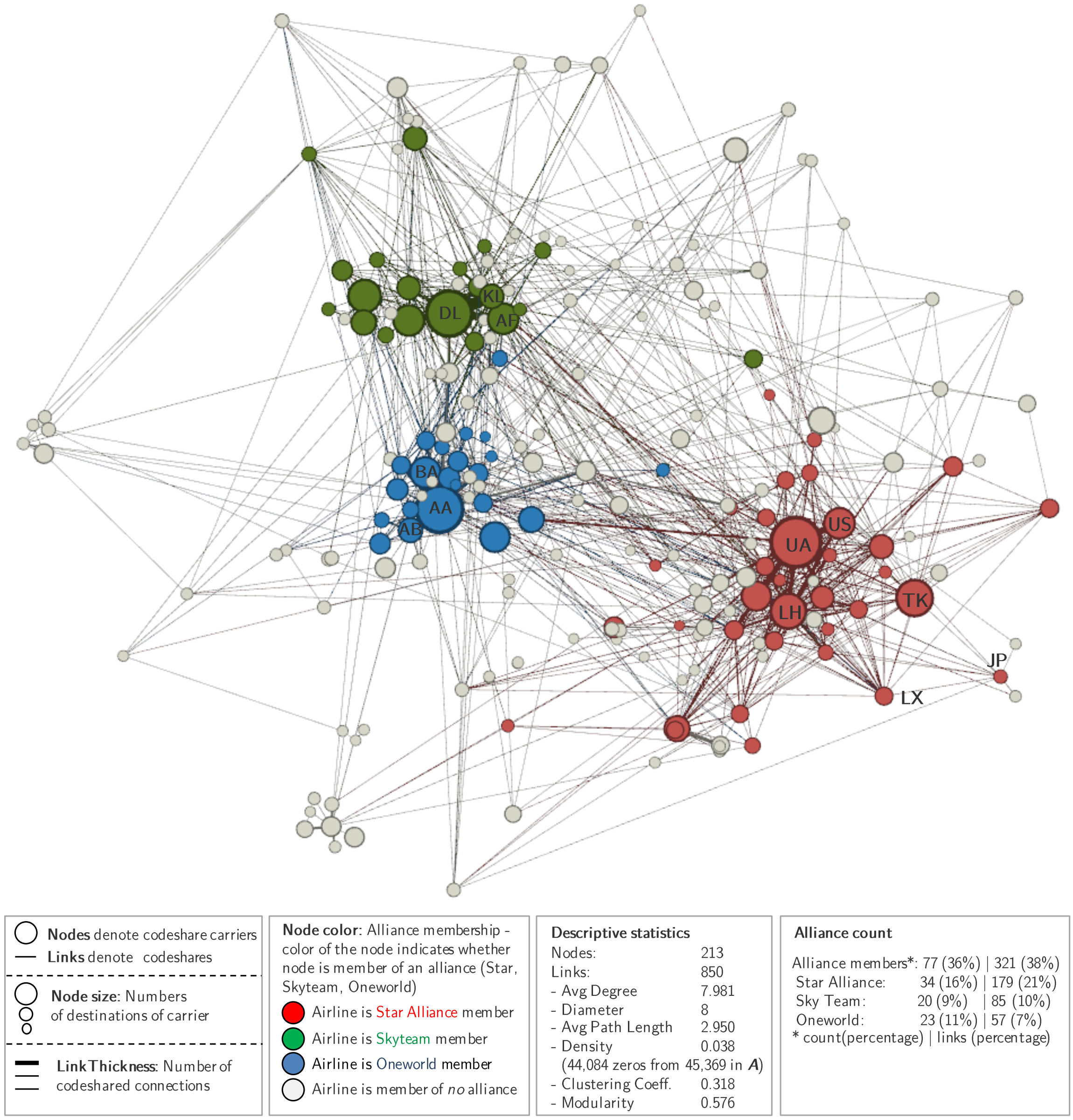

Figure 43. *Alliances in the network of codesharing airlines as of January 2012*

I specify how to operationalize *the core* in the codeshare network. We see from the network plot that clusters within the core and major alliances (Star, Sky, and One) strongly overlap. Additional analyses hence tried to illuminate whether the network may be better understood as a *preferential attachment* network. Under preferential attachment, several hubs come to exist that are complemented by a large number of spokes. This results in a "power law" degree distribution in which central nodes accumulate a higher number of linkages than would be expected in random networks equipping the degree distribution with a "fat tail" (Barabasi and Albert 1999; Jackson 2008b). To examine my presumption, I plotted the log-logged degree distribution (refer to Figure S7 in the appendix). Eyeballing the data built trust in the fact that there is a linear relationship between node's logged degree and their logged relative frequency as expected for a preferential attachment model (cf. Jackson 2008:130-134). The good fit of a linear regression further strengthened my presumption that the network exhibits a preferential attachment structure ($R^2 = 0.798$, F

= 122.723, $p < 0.001$). Therefore, one can discuss the model against the backdrop of preferential attachment networks.

7.2.2 Segment-Level Analysis

To evaluate further whether linkages remain mostly within airline alliances ("*inside-in*") or whether a significant share of linkages go to the remaining network ("*inside-out*"), I used a *blockmodeling approach* (Borgatti and Everett 1992). As a first step, I defined the alliances as blocks. Then, I designated *inside-in linkages* as those that stay within one block while inside-out linkages span from one block to another. Rearranging the codesharing matrix $\boldsymbol{A}$, the modeling aimed at four blocks: Star, Sky, One, and the other block.

Figure 44 depicts the fraction of linkages remaining within a particular alliance (inside-in) versus the linkages that span from one alliance to members of another alliance or non-alliance members. In a block model, one would expect that particular blocks would be strongly wired but not wired to the outside blocks. We see that, within the Star Alliance block, the share of inside-in and inside-out linkages is almost balanced (47 percent versus 53 percent) while the other two alliances have significantly lower inside-in ratios. For Sky Team and Oneworld, the fraction of inside-in versus inside-out linkages is about one-third against two-third. As expected, the fraction of inside-in linkages is lowest for non-alliances members. As codesharing is a practice that was developed in an alliance context, often at least one codesharing party is organized in an alliance (cf. Hu et al. 2013).

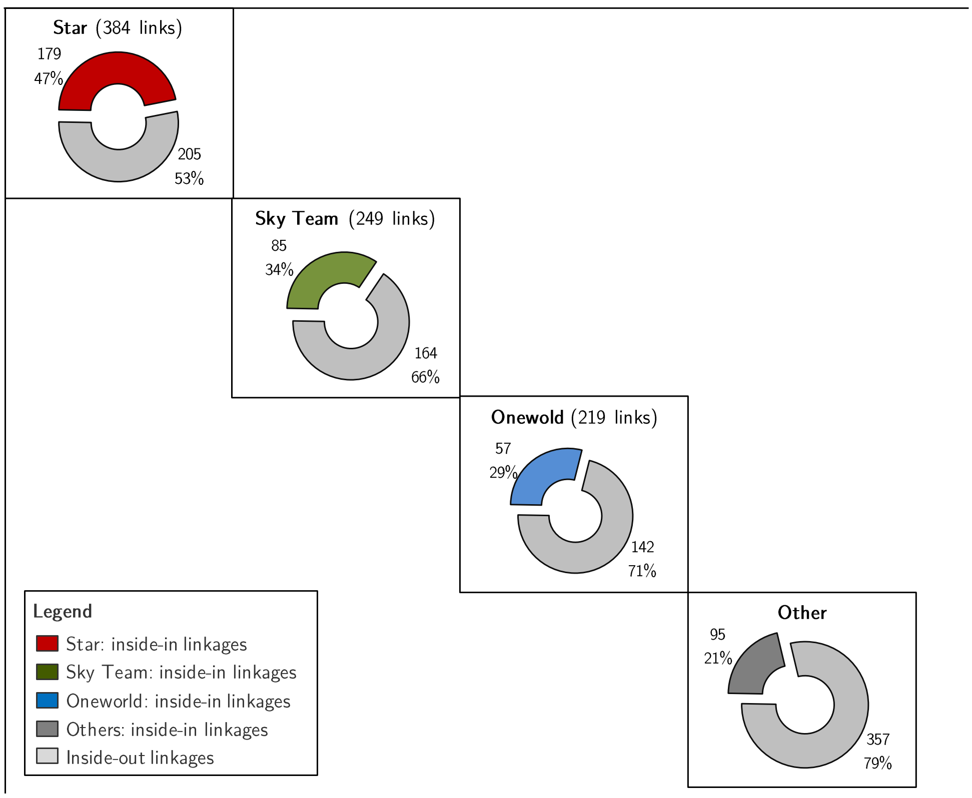

Figure 44. Share of inside-in versus inside-out linkages

This figure shows that the fraction of inside-in linkages is highest for Star Alliance (about one-half) and comparatively lower for the other alliances and the others group.

7.2.3 SWISS as an Example for Improvisational Capabilities

We begin our micro level analysis by turning to the example of SWISS. As a first step, we contrast SWISS with selected other carriers. In Figure 45 – an extract of the network plot zoomed and filtered with respect to SWISS' positioning in the network – we see that SWISS links most intensively with close-knit partners of the same alliance; it is part of a densely connected group of Star Alliances members (e.g. Lufthansa/LH, Brussels, Air Canada, United, and Austrian). A limited number of links span across alliances.

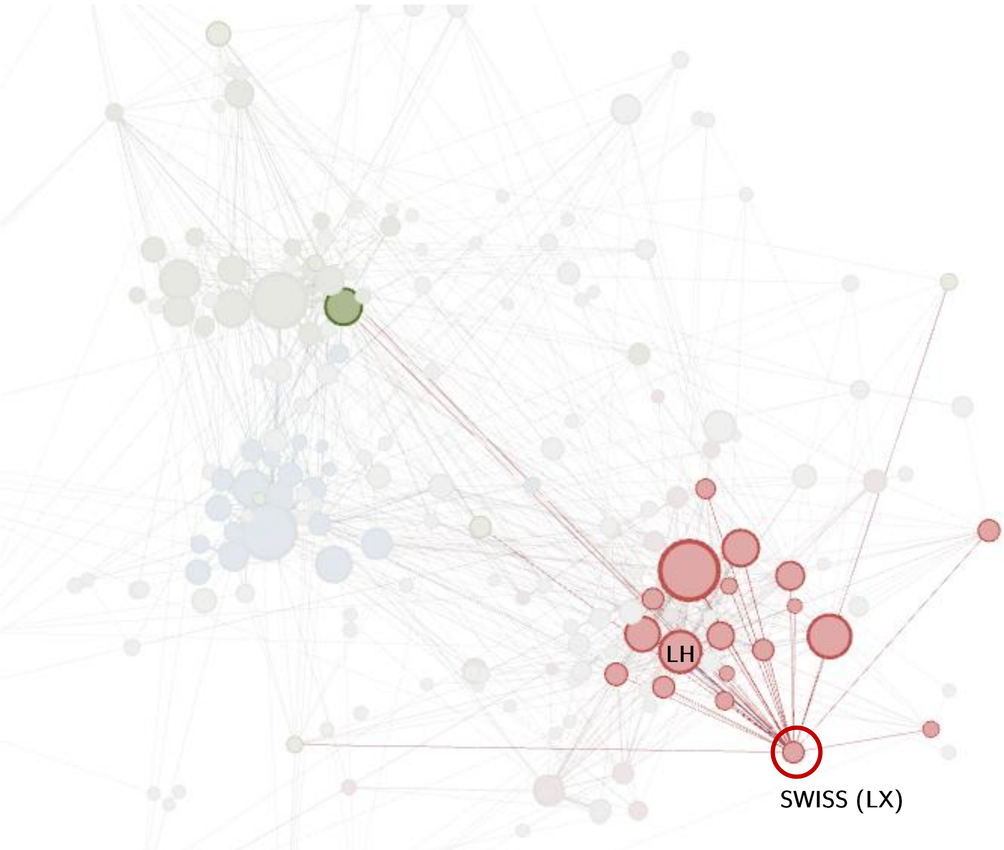

Figure 45. *Embeddedness of SWISS in codeshare network*

This figure shows the positioning of SWISS in the codeshare network. The colors of the nodes denote the alliances; reddish nodes belong to Star Alliance, greenish nodes belong to Sky Team, and blueish nodes belong to Oneworld.

Table 23 compares SWISS and Air Berlin with respect to selected measures of centrality. As both are mid-sized carriers, I added Lufthansa as an example of a large carrier. SWISS codeshares with 26 other entities; this indicates above-average embeddedness in the network. When we take into account the intensity of collaborations however, we see that the overall number of codeshare routes is only slightly above average. I suspect that the carrier's regional positioning is a natural limit. Comparing these results with Air Berlin's confirms the impression that SWISS is more intensively embedded but also more specialized to particular customer segments, geographical destinations, and markets.

Table 23. Selected measures of centrality for SWISS and two other airlines

	SWISS	Lufthansa	Air Berlin	Mean
Destinations	76	236	134	56.042
Degree	26	33	13	7.981
Weighted degree	115	1,032	264	97.906

I further detail the example of SWISS. The account of SWISS illustrates two main pieces of my argument: that codeshare interaction patterns matter for the scope of action in adopting a new standard and that a firm’s improvisational capabilities can be undermined by spillover effects from its network embeddedness.

I proceed by turning to SWISS’ organizational IT infrastructure. Consistent with my overall approach, I model it as a network. In Figure 46, nodes represent applications interacting with each other. Links materialize in flows of information. For reasons of clarity, I focus on selected aspects of the IT landscape that are most relevant for my study. In particular, I concentrate on distribution and pricing and abstract away systems in the area of airline operations. For important nodes, I gathered data on information flow directions.

Of the several systems depicted in Figure 46, two are most relevant for my study: the host inventory in the center, with strong ties to almost any other system, and, most importantly, the Real-time Dynamic Pricing Engine (RTDP) at the bottom.

The host inventory is the most critical IT resource in SWISS’ IT infrastructure and many other systems build upon it. SWISS’ predecessor Swissair was an early leader in retail automation; it replaced its original CRS, implemented for SWISS’ sales offices 1972 (Schulz et al. 1996:53), in the 1980’s with another SABRE-branched CRS, which is still operational today. The system – previously managed by the former IT unit of Swissair Atraxis – is now operated by HP. The system integrates ticketing, distribution, and pricing very tightly and efficiently; in addition, it interoperates smoothly with several GDS. According to interviews (refer to RM experts in oS8-10), the inventory is an important link to the outside world as well as a major antecedent for additional marketing and pricing models building on top of it. The GDS connects in real-time to SWISS’ host inventory for each agent request – using a mechanism called “seamless availability” (Isler and D’Souza 2009:259f.). The host inventory determines the availability status and responds back within seconds. This is possible with reasonable effort even in an origin and destination network context as the network optimization problem has a “relatively simple structure” (Isler and D’Souza 2009:260). Most relevant for my study is that booking classes are deeply inscribed in the system. They are most pervasive in ticketing and for fare product functionality managed by the system (refer to RM experts in oS7 and oS8).

Another important IT resource to support SWISS’ advanced pricing capabilities is its RTDP. Essentially, the system is responsible for updating availabilities of fares based on the results of forecasting and optimization. In 2003, a project at Swissair introduced an origin and destination-based revenue management system. After SWISS was founded, the project was re-launched and the system went live (refer to RM expert in oS7). The RTDP was constantly advanced over a “good last decade” in close collaboration with an American software vendor (refer to RM expert in oS11). Additional functionality was moved over from SWISS' host inventory and integrated in the RTDP; for instance, the availability calculator or the connection builder (CB).

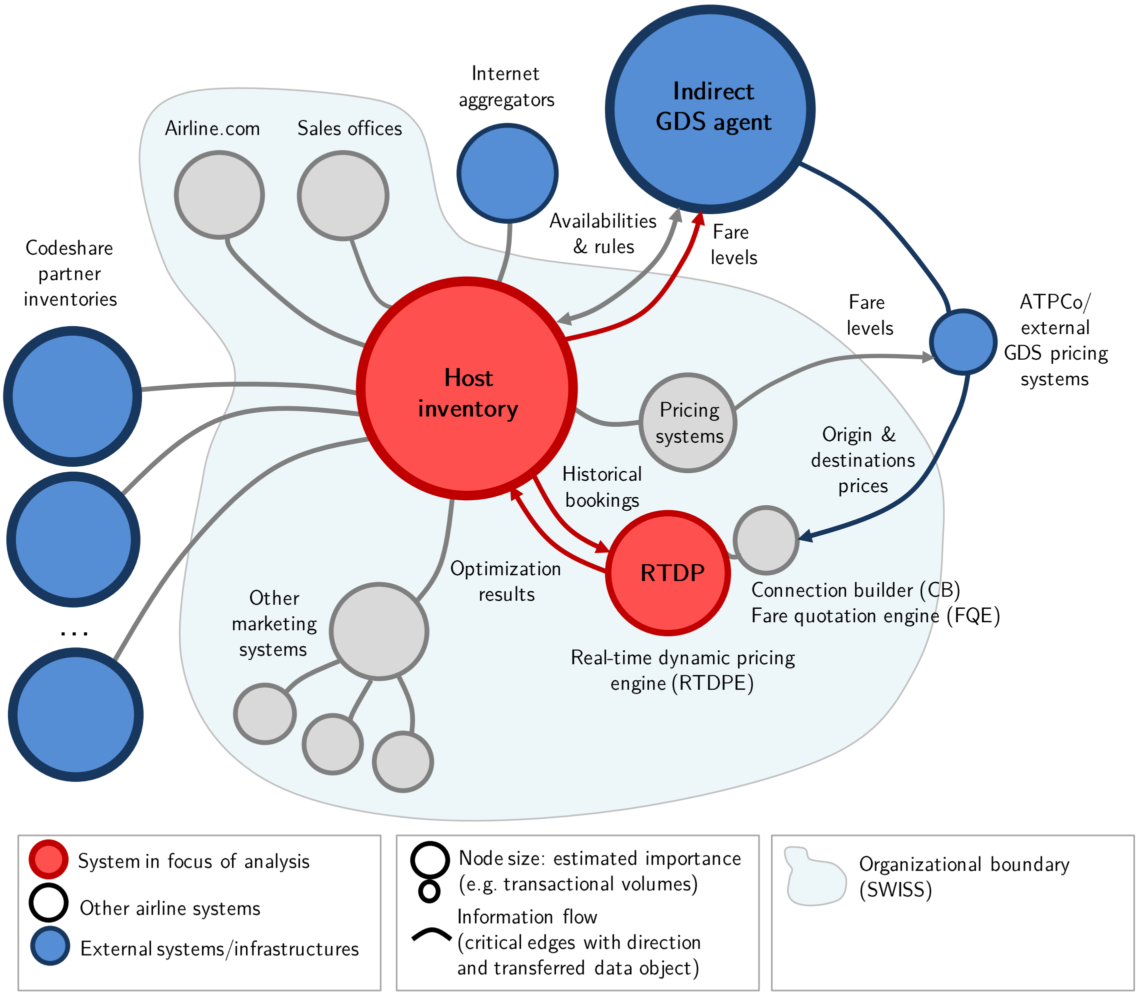

Figure 46. SWISS' distribution and pricing IT landscape. Source: own investigation

This figure shows central IT systems and their linkages in the area of distribution and pricing in SWISS' IT landscape. The figure was compiled using field data, i.e. oS34.

Based upon this infrastructure, SWISS could build advanced dynamic pricing capabilities, starting to control not only seat availabilities but also price availabilities on a booking-class level. In particular, dynamic pricing (with continuous price points) represents another technical refinement of bid pricing (refer RM expert in oS7 and memo oS31): fare availability is controlled on the level of particular booking classes (refer to expert statement in oS31). Particular fares are utilized to determine the value of a booking class. This value is both used in the online mechanisms – responding prices to trip requests directly – and for computing bid prices. Revenue management then concentrates on the optimal availability of fares by switching particular booking classes on and off selectively. This is expected to enable price discrimination according to customer characteristics (e.g. length of stay, frequent flyer tier level, advanced purchase) better than predetermined fare conditions associated to a fare. Most preferably, only one fare is published per booking class (refer to memo oS31). But at least fewer fares are used for segmentation.

Supported by SWISS' improvisational capabilities, several initiatives have been started to work around the limitations of the booking class standard. For instance, a project was launched in 2013 to reengineer the group booking process. The idea was to gain more independence from booking classes by not using another booking class for groups but instead to evaluate all group bookings together based on their value. In this way, SWISS aims to calculate the optimal group price as a "spot price" based on an instant quote for a particular group and its particular requestor, which is offered only then, with a value that differs from the APTCo-filed fare (refer to RM experts in interview oS8 and oS9). Traditionally, airlines have utilized GDS components for this task (refer to interview oS20) and moving to more independence requires in-depth insights into how to build connections in a large origin-destination network finding the cheapest applicable fares for those connections. As a first step, the company aims at replacing the usually heavy-machinery "host"-based building process in use today with an XML interface that scales to significantly larger request volumes.

Initiatives to work around the limitations of the booking class standard are, however, undermined by SWISS' embeddedness in existing distribution networks. Beyond GDS restrictions, requirements to conform to predefined standards also arise in the context of alliances and joint ventures. A pertinent example is when SWISS' had to reintroduce more complex fare structures when it entered the Atlantic Joint Venture in 2009. A revenue management expert reports:

> *"On intercontinental routes, I had to replace particular pricing methods, because we joined the A++ transatlantic joint venture. Because [..] when you want to harmonize prices, and certain carriers, [..] they do not even have an origin destination system. And what you cannot do is simply to adopt these fare structures, if you do not have the subsequent machinery"* (revenue management expert; refer to interview oS7)

The consequences of codeshare agreements for SWISS become most visible when we turn to the left side of Figure 46. For each codeshare agreement, a class mapping is agreed with the particular partner, integrating inventory systems on a technical level. From this a situation follows in which multiple airlines have to be integrated, which is often achieved using booking classes as a "smallest common denominator" (refer to RM experts in oS8).

7.3 Contagion Model

Based upon the requirements from the empirical problem instance (refer also to chapter 1.1), I proceed further by introducing a model of contagion simulating how a new standard cascades through a network of codeshare linkages to assess whether such a new standard will come to diffuse to a nontrivial fraction of agents.

7.3.1 Triggering Events and Contagions

Figure 47 depicts the dynamics of the network analysis starting with a matrix of linkages among n agents. Individual agents hold the attributes *size* and *alliance membership.* The analysis consists of simulating triggering events ("shocks") to a specific agent (the "trigger airline") and tracking the domino effect to other agents in the network.

Algorithm A.8 describes the steps carried out throughout the network analysis. After having initialized the network, the algorithm proceeds as follows: I trigger a cascade by selecting one agent/node uniformly at random that I switch to the new standard (*trigger-switch*, lines 2-10). This node is classified as *reached*. Then, in the internal loop (lines 11-27), I collect all neighbors of the trigger node and store them in a list of direct neighbors. This list holds all neighbors of the trigger node within a distance of one step. The cascade is now running and a counter of the contagion round (*cround*) is initialized with the value of zero. Starting in the first contagion round, I then assess for each node in the direct neighborhood whether each of these nodes will switch to the new standard given particular threshold-specific rules described below. Next, I perform a further, radial search (lines 28-39) for each of the direct neighbors of the first-order neighbors and store the second-order neighbors of each of the first-order neighbors in another, temporary list (*wait-lst*). The temporary list then replaces the initial list of first-order neighbors. Then, the count of the contagion round is increased by one. The contagion rounds continue until all nodes in the network have been assessed or until no further nodes in the component of the trigger node remain. After each cascade, defined as an intervention and the subsequent contagion rounds, the algorithm converges (lines 40-48): The trigger node itself assesses whether it should stay with the newly explored standard or whether it should return to the old standard (line 45). This is done by performing the *check-switching* operation. After each cascade, the fraction of nodes having switched to the new standard is measured and the network is reset (lines 46-47). If the target level is not reached, a new cascade is triggered in the same way.

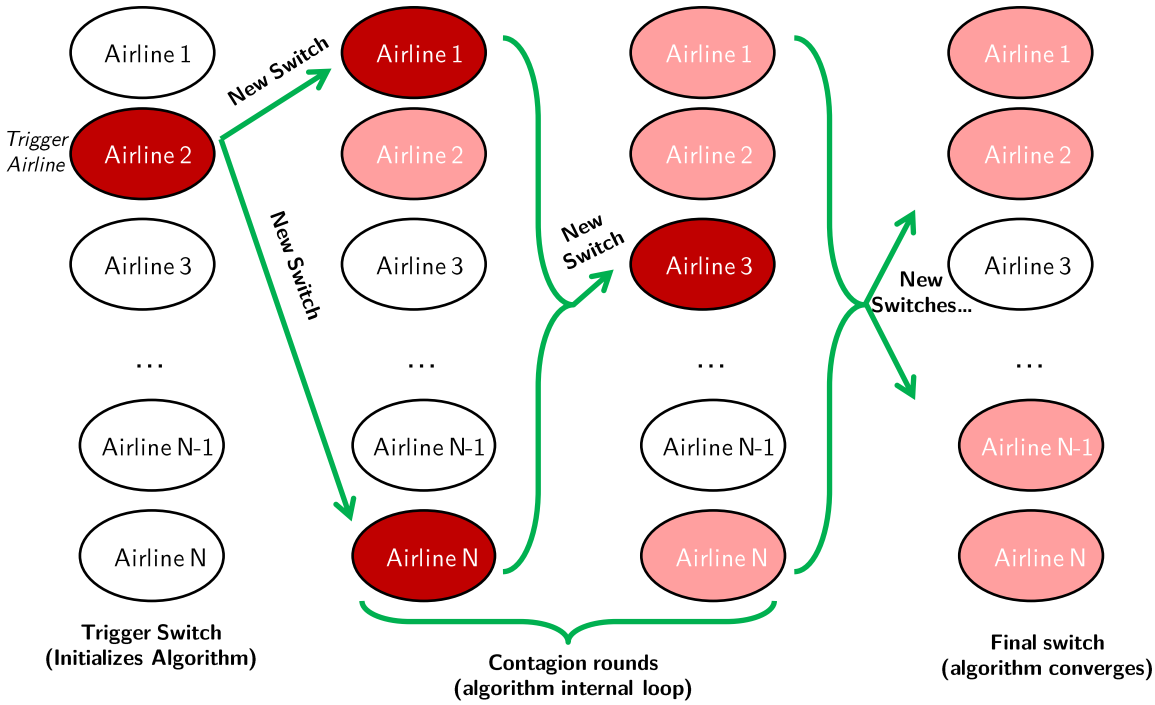

Figure 47. Network analysis: assessing the role of linkages for the standard's spread

Note that the figure was adapted from IMF (2009:78), where a similar algorithmic idea is used to assess to the systemic implications of financial linkages in the banking sector.

Algorithm A.8 Network analysis

```
irunning? := false
to trigger-switch
  if not irunning? then
    for one-of nodes with technology not 'new' do
        trigger-node := true, technology := 'new', reached? true
        lst-radius1 := all nodes in radius 1 without trigger node
        irunning? := true, cround := 0
   end for one-of nodes
  end if
end trigger-switch
to internal-loop
  if irunning? true then
    if cround > 0 then
      if length lst-radius1 = 0 then converge-algorithm
      else
        i := 0
          while i < length lst-radius1 do
                foreach node from lst-radius1 do check-switching, reached := true
                end foreach
            if any? unreached? node then lst-radius1 := radial-search lst-radius1
            else converge-algorithm end if
            cround := cround + 1
          end while
        end if
     else cround := cround + 1  // to start the first contagion round in next period
    end if
  end if
end internal-loop
to radial-search
  wait-lst := [ ]
  if not any? connectable-nodes then converge-algorithm
  else
    foreach node from lst-radius1 do
      foreach node in radius-1 do
        if not 'reached' of item i sort nodes in radius 1 then put item i on wait-lst
      end foreach
    end foreach
    remove duplicates from wait-lst, report wait-lst
end radial-search
to converge-algorithm
  j := 0
  while j < length lst-radius1 do
     foreach item lst-radius1 do check-switching end foreach
  end while      // trigger node may stay with the new standard
  foreach node with trigger-node = true do check-switching end foreach
  lst-radius1 := [], cround := 0, irunning? false
  foreach node do reached? := false end foreach
end converge-algorithm
```

An alternative intervention strategy, although not yet systematically explored, is put forward by Jackson (2008b). He suggests shocking nodes with high degree, betweeness, or Eigenvector centrality. In a later section, I modify the model with respect to alternative intervention strategies that target particular groups of agents such as alliances or maximum cliques.

7.3.2 Adoption Rules: Individual-Level Thresholds

In agent-based simulation research, often simple rules on the micro level create complex, emergent outcomes on the macro level (Gilbert and Troitzsch 2010; Holland 1995). I use individual-level adoption thresholds to guide agents' adoption behavior as they are superior to collective thresholds in creating emergent outcomes (cf. Valente 1996). Adoption thresholds condense important information about an agent's state such as the agent's switching costs and benefits. If a predefined threshold is exceeded, agents will adopt the new standard. Otherwise, they stick with the old standard. To assess whether an agent will adopt, I introduce the following simple rule:

Codesharing rule: *Adopt if a fraction of your codesharing partners adopted that is equal or larger than your threshold (θ).*

where $\theta \in \mathbb{R}$ and $0.0 \leq \theta \leq 1.0$. This simple threshold rule takes into account imitation across peers and is expected to produce contagious dynamics following from spillovers from one agent to another[19]. For a threshold θ of 0.5, it can be considered as a *majority rule* (cf. Narduzzo and Warglien 1996) in which agents adopt if most of the agent's partners have adopted.

Consider the following simple example. An agent with three partners assesses whether a switch to the new standard is beneficial. First imagine that, two partners of the agent have already adopted. For a threshold $\theta = 0.5$, the agent would then also adopt, as two-thirds is larger than the majority and thus the threshold is exceeded. For $\theta = 0.3$, the individual agent's threshold is also exceeded and the agent would also adopt. For $\theta = 1.0$, the agent would not adopt; only if all three partners of the agent had adopted, would the agent participate in the initiative.

[19] Note that, in this simple threshold model, I assume homogeneous thresholds for all agents in the population. In a later stage, I relax this assumption taking into account heterogeneous thresholds across agents. In particular, I consider individual agent sizes relative to the agent's peers (size-adjusted threshold) and individual agents' collaboration intensity from weighted links (weight-adjusted threshold).

Chapter 8

Insights from Agent-based Simulations: Contagion

8.1 Computational Implementation of the Contagion Model

The model was implemented in Netlogo 5.0.3 (refer to code example oS5 and chapter 5.1 for a general introduction of the simulation environment). I draw on the new network extension (Netlogo 2014) that was particularly useful for the implementation of the contagion model as it eased graph distance calculations and group detection in graphs.

8.2 Theoretical Validation and Verification

The next sections present baseline results for archetypical networks and reproduce findings from seminal diffusion models.

8.2.1 Baseline Results for Archetypical Networks

The easiest way to illustrate how the adoption dynamics unfold in the model is cellular automata. A cellular automata consist of a number of identical cells arranged in a regular grid (Gilbert and Troitzsch 2010:131f.). Cellular automata can also be re-conceptualized as a network of nodes on a (spatial) lattice with a regular number of neighbors. I assume that the number of nodes in the network is finite and the edges are not connected. In our simple cellular automata, each cell has only two states: either it adopts the standard (1) or not (0).

Based on this notion of cellular automata, we can discuss how the model unfolds for different structures and adoption thresholds. Think first of a one-dimensional cellular automata with five cells (cf. Figure 48a). I label these cells $i_1,..,i_5$. If we assume that initially all cells are 'off' (0), how long will it take until the standard diffuses for different threshold values? Let us examine extreme cases where the adoption threshold is zero and one. For $\theta = 0$, a triggering event that switches one cell *on* (1) uniformly at random, would cascade to all immediate neighbors in one step – it switches them on, cascades to the next set of immediate neighbors and would terminate in a maximum of four steps (if it came to trigger i_1 first). One shock will suffice. For $\theta = 1$, immediate neighbors of a triggered cell will only switch if our observer came to penetrate a cell one step next to the edge (i_2 or i_4). In this case, the cell on the edge (i_1 or i_5) changes its state from *off* to *on*. A minimum of two shocks is required if both close-boarder cells came to be penetrated within the first two interventions. Drawing on the terminology by Liu et al. (2011b), I denote these "close-boarder" nodes as *unmatched nodes*.

I move on to a more complex cellular automata with cells arranged as a rectangular array (cf. Figure 48b). The graph is now cyclic. I start with a square of four cells $i_1,...,i_4$. An intervention for $\theta = 0$ will change all states to *on* after the first shock has cascaded in two rounds. A shock for $\theta = 1$ will have no effect as each cell is surrounded by two neighbors: as one of its neighbors is *on* while the other one is *off*, immediate neighbors of a triggered cell will not switch. This remains true for any threshold above 0.5. Below this threshold, immediate neighbors will switch as seen for $\theta = 0$. An even more complex cellular automata with nine cells (cf. Figure 48c), $i_1,..,i_9$, yields qualitatively different results due to the fact that the cell in the center has exponential requirements regarding the number of immediate neighbors that have to change states before it switches. For $\theta = 1$, four neighbors (instead of two in the case of four cells) have to adopt the standard before the cell in the center switches.

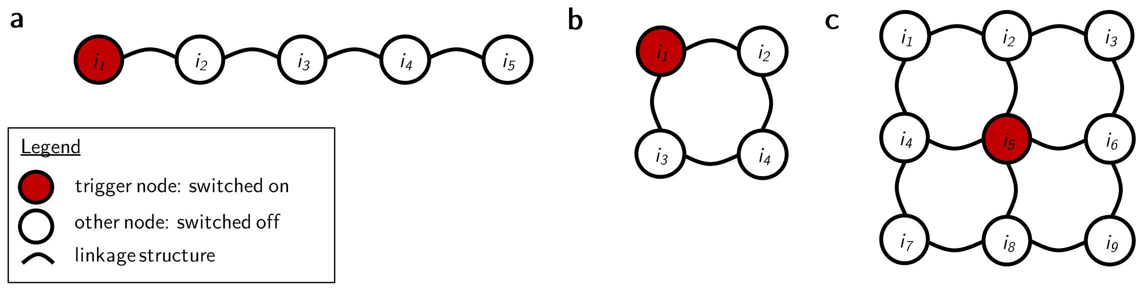

Figure 48. Adoption dynamics in networks with regular, cellular automata structure

To discuss structural differences across networks in more detail, I refer to a fully-meshed network (cf. Figure 49a), a preferential attachment network (cf. Figure 49b), a star network (cf. Figure 49c), and a tree network (cf. Figure 49d). Let us start with a full density network (cf. Figure 49a) and $\theta = 0$. Think of four nodes $i_1,\ldots,i_4$ where each of the nodes is wired. Given a shock to a random node i_1, the new standard propagates immediately along the paths i_1i_2, i_1i_3 and i_1i_4 to all nodes in the network. In the example, the convergence time is one and the number of shocks also equals one. This can be generalized for each number of nodes in a fully meshed network. If $\theta = 1$, each initiative dies out quickly for $n \geq 2$ as each node has several neighbors (exactly it is $n - 1$) of which only one has adopted. Hence, the system does not converge for any number of shocks.

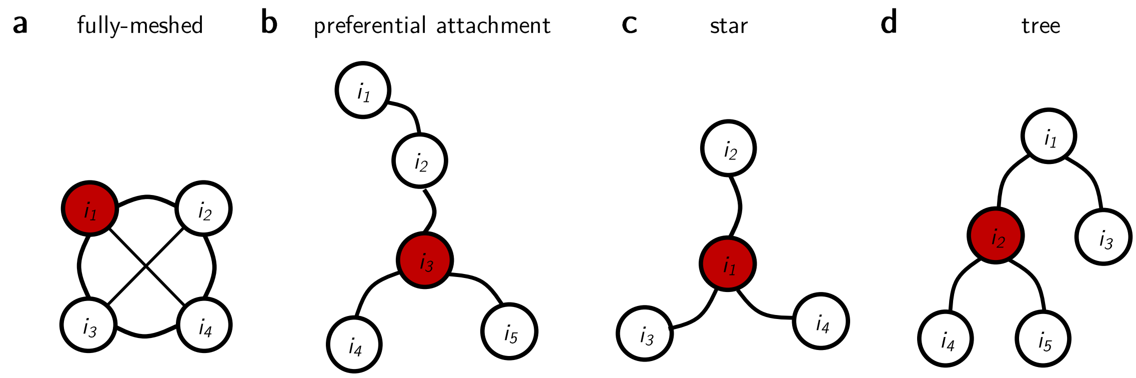

Figure 49. Examples for adoption dynamics in different networks

I move on to a preferential attachment network (cf. Figure 49b) and $\theta = 0$. The rule holds that nodes switch for any number of neighbors having already adopted. Given a shock to a random node i_3, in the first contagion round, the new standard propagates along the path i_2i_3, i_3i_4, i_3i_5 through the network. In the next contagion round, the standard travels along the path i_1i_2 to the last remaining node i_1. The convergence time equals the length of the shortest path to any other node in the network; it is two in our example. The system converges (always) after one shock. For $\theta = 1$, the trigger node only switches any other node if a close-boarder node such as i_3 or i_2 is hit. I turn to star networks to illustrate this in more detail.

Consider a star of four nodes with a center i_1 as shown in Figure 49c. I assume that a node switches only if all of its neighbors adopted ($\theta = 1$). Then, there are two types of nodes: the center and any other node. In the example, the center i_1 is only adjacent to peripheral nodes that switch immediately after i_1 has been shocked. The network converges after one shock. Consider as another example a tree with two layers (cf. Figure 49d): i_1, the root, i_2 and i_3 on the first layer and i_4 on the second layer adjacent only to i_3. The network converges after a minimum of two shocks to i_2 and i_1. This is the case as there are (*i*) unmatched nodes and (*ii*) matched nodes. Unmatched nodes are defined as nodes being adjacent to peripheral nodes that are only connected to this particular node *or* that have only further peers that have already switched. Shocking an unmatched node will affect the state of the network; peripheral nodes will switch. This may change the state of the network as unmatched nodes will maybe become peripheral, matched nodes. Think of a shock to i_3, which triggers a switch of i_4. Only then will a shock to i_1 trigger a switch of i_3 (who went back to the old standard according to the definition in Algorithm A.8) and i_2. In general, the probability triggering an unmatched node will decrease proportional to the network size. The system only converges if it is tree-like, meaning that a search could propagate backwards through the network until it reaches a root node. This is, for instance, the case for trees and stars but will seldom be the case for random networks. Hence, the lower limit to the number of shocks is determined by the (recursively defined) number of unmatched nodes in the network. It is two in our example; first i_2 must be shocked and then i_1 (cf. Figure 49d).

8.2.2 Equilibrium Existence

There exist solutions where (*a*) no agent adopts, (*b*) an incomplete fraction of the population adopts, and (c) all agents in the population adopt.

Imagine first a fully-meshed network with four nodes (i_1,..,i_4). As shown in Figure 49a, the new standard will not diffuse as each intervention peters out immediately after its initialization. The strong integration among peers inhibits adoption of the new standard.

As a next example, think of a network in which we add one node (i_5), wired only to i_4. If a spontaneous innovation is triggered at i_4, the newly added node i_5 adopts the new standard. All remaining nodes stick, however, with the old standard and the fraction of adopters will settle at one-fifth of the population. Standard diffusion remains local and thus partial.

Imagine, as a third example, that we remove only one edge ($i_1 i_4$) from the network. After i_5 has adopted, shocks to either i_2 or i_3 will trigger a switch of i_5. Subsequently, i_3 adopts and then finally i_1 and i_2. The entire population moves to the new standard. Standard diffusion is complete.

Based upon these three states, I proceed further by illustrating the existence of solutions with non-complete adoption rates for random networks. I set up experiments with random networks under different link probabilities (λ). Figure 50 shows one sample run where the new standard did plateau after initial diffusion to a fraction of about 15 percent of all agents. It illustrates that standard diffusion may settle at a non-complete fraction of the population.

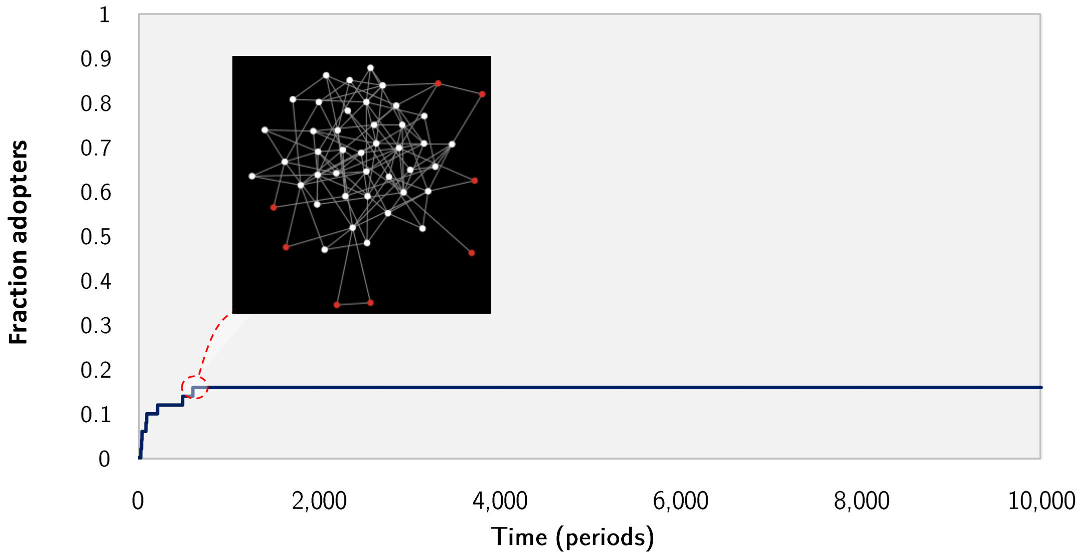

Figure 50. Incomplete diffusion in one sample run of the simulation

This figure shows the adoption dynamics for one sample run in a random network with n = 50 nodes and a link probability of λ = 0.09. The adoption threshold was set to a medium level (ϴ = 0.5). The simulation was stopped after 10,000 periods as no further dynamics could be observed.

8.2.3 Replicating "S-Shaped" Diffusion Curves

A next set of experiments aimed at replicating the "S-shaped" diffusion curve from diffusion theory (Rogers 2003). According to this view, initially, a few innovators adopt early, then diffusion increases in speed due to word-of-mouth or observations by others, and eventually adoption slows down as the market saturates (Jackson 2008b).

To reproduce this stylized fact, I set up experiments drawing on random networks and medium adoption thresholds (θ = 0.5). Random networks serve as a useful baseline that enable benchmarking results for different degrees of connectedness (Jackson 2008b), expressed by the link probability (λ).

Decreasing the link probability (λ) in steps of 0.01, I found that S-shaped diffusion curves were most likely for n = 50 nodes in a small interval between λ = 0.07 and λ = 0.04. For higher values of λ, the network did not converge as the dense linkage structure prevented that the new standard gained momentum. For low levels of λ, below 0.04, the network was disconnected and the new standard could not spill over to isolated nodes.

Figure 51 shows one example in the middle range (λ = 0.07) where I could observe a diffusion curve that reproduces the expectations from diffusion theory. During the first 100 periods few agents adopt, then the standard gains momentum and spills over. Finally, the "laggards" adopt.

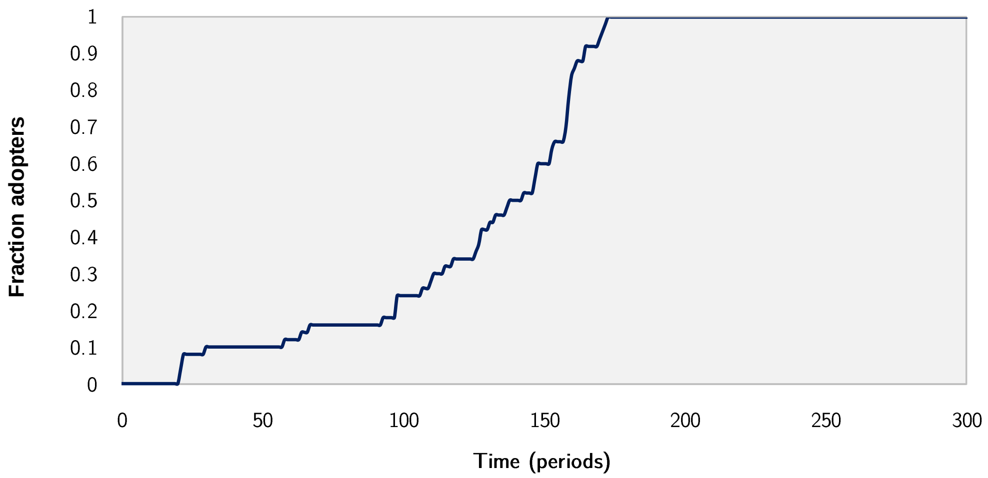

Figure 51. *Replication of S-shaped diffusion curve*

This figure shows adoption dynamics for one sample run in a random network with $n = 50$ nodes and link-probabilities of $\lambda = 0.07$. The adoption threshold was set to a medium level ($\Theta = 0.5$). The simulation was stopped after 300 periods as the entire population adopted.

8.3 Results: Assessing Scenarios for a New Standard's Diffusion

The next sections present simulation results using different configurations and intervention strategies to examine under what circumstances the new standard diffuses to a nontrivial fraction of agents.

8.3.1 Experimental Setup and Measurement of Convergence to Target Level

I define a fraction of 75% adopters as the baseline to assess whether a nontrivial fraction of agents was tipped for the particular configuration of the system where a binary variable *target level* is one if this is the case and zero otherwise.

Fraction adopters: As agents may return to the old standard after having assessed the new standard (refer to Algorithm A.8), the system may not converge to the target level. Hence, I report the fraction of adopters either 250 ticks after the target level was reached or at the end of each simulation run. Following the procedures described in Law (2007:488 et seq.), I set the simulation's time limit to 7,500 periods.

Timing of tipping point (timing TP): I report the number of contagion rounds until the target level is reached (for convenience often abbreviated as *time/periods* as it equals the simulation time). As tipping points in almost all cases occurred shortly before the target level is reached, we can approximate the timing of the tipping point by this measure.

Shocks target: As often times multiple shocks will be necessary before the system converges, I also report the number of cascades running through the system until it converges to the target level. As the network diameter is 8, the number of shocks will be a maximum of one-eighth of the number of periods in the simulation environment.

Intensity of the tipping point (intensity TP): To map the relationship between the adoption threshold (θ) and strength of the tipping point, I implemented a measure taking into account the differences in (relative) adoption between two subsequent cascades. For each cascade, I recorded the fraction of adopters after the end of the cascade. The model then computes the differences between adopters in this cascade in comparison to the adopters after the last cascade. From this list, holding the differences in the fraction of adopters for each cascade, I compute the maximum. In case a tipping point exists – indicated by the binary variable *target level* – the amplification of the tipping point is the maximum value in the vector of differences in adoption. This designates the *intensity of the tipping point*.

8.3.2 Simple Thresholds: Exponential Increases Due to Power-Law Structure

I now turn to a first set of simulation results using data on the real codeshare network. Drawing on the simple threshold model, I report whether the system exceeds the predefined target level for varying adoption thresholds (θ). I performed additional experiments on theoretical network structures (i.e. random networks with varying link probabilities, preferential networks, lattices, and star networks). Refer to Table S22 in the appendix for complete results.

Figure 52 depicts three sample runs for – what I defined as – a low, medium and high threshold (θ). In the example, a medium threshold level ($\theta = 0.5$) portrays a situation in which an agent switches to the new standard if the majority of its partners switched. We see that for a medium and high threshold, the network will not converge to the target level. For a low adoption threshold ($\theta = 0.3$), we find an *S*-shaped diffusion curve (cf. red line in Figure 52): adoption dynamics unfold slowly during the first 500 periods (contagion rounds, which equals around 30 to 50 shocks) but after the system has exceeded an adoption rate of about 30 percent, a tipping point occurs; almost the entire remaining population adopts. We see a sudden and abrupt change within one or two cascades.

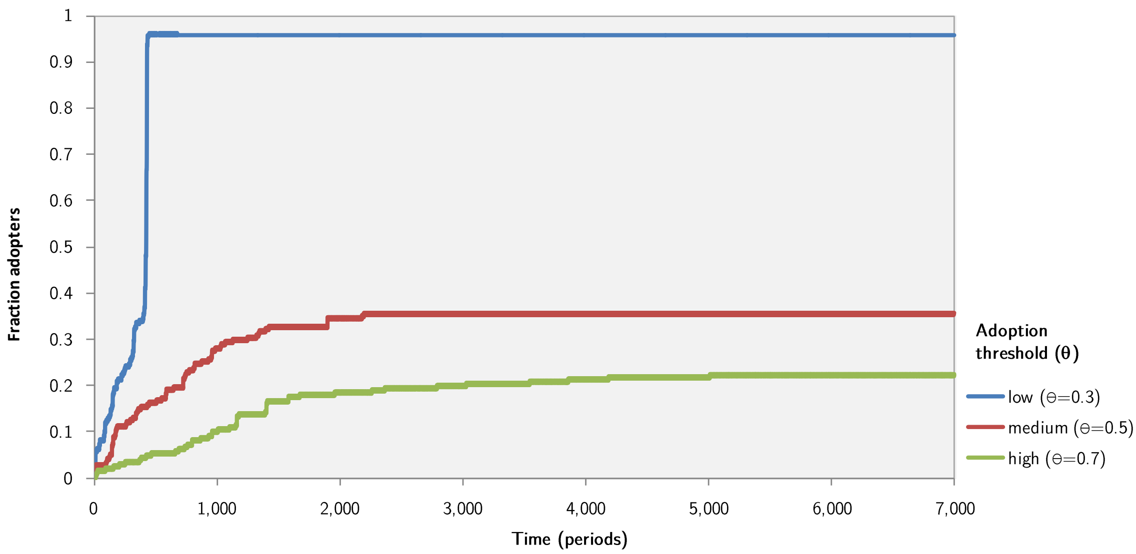

Figure 52. Adoption dynamics for varying thresholds

Table 24 reports the complete results. An investigation of the column $\theta = 0.3$ and $\theta = 0.4$ gets quickly to the main finding: For smaller values of θ, the target level of 75% is exceeded and most airlines adopt. For larger θ values, the standard plateaus at 40% or less. Corresponding to these findings, the fraction of all airlines by size also, as shown in the fourth row, exceeds the target level for low threshold levels, while it remains marginal for medium and large threshold values. Table 24 also offers a valuable vantage point from which to investigate the amount of interventions necessary to tip the system: while a triggering event that penetrates two or three airlines will suffice for $\theta = 0.1$, the number of shocks increases exponentially with increases in the adoption threshold θ. An inspection of the last two rows expresses this finding: the number of shocks increases from one to ninety-six.

Table 24. Results for varying levels of simple adoption threshold

	Adoption threshold[1,2,3] (θ)										
	0.0	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1.0**
Target level?	yes	yes	yes	yes	no	no	no	no	no	no	no
Adopters (%)	0.958	0.958	0.958	0.958	0.408	0.352	0.220	0.221	0.220	0.220	0.220
Std. dev.	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.001	0.001	0.002	0.002
$\text{Adopter}_{\text{size}}$(%)	0.979	0.979	0.979	0.979	0.216	0.158	0.082	0.082	0.082	0.082	0.081
Std. dev.	0.006	0.005	0.005	0.005	0.000	0.000	0.000	0.000	0.000	0.001	0.001
Timing TP	3.59	18.66	73.86	523.86	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Std. dev.	0.68	6.99	28.58	144.21	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Shocks target	1.08	3.79	13.98	96.470	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Std. dev.	0.27	1.233	5.232	26.626	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Intensity TP	0.95	0.70	0.53	0.32	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Std. dev.	0.00	0.12	0.09	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00

[1] Target level was 75% of the population and the simulation was terminated if this level was exceeded
[2] Average results for 100 simulation runs
[3] The time limit of the simulation was set to 7,500 ticks; *n/a* denotes non-converging cases

Figure 53a depicts the distribution over outcomes for the four thresholds ($\theta = 0.0, 0.1, 0.2, 0.3$) at which the system converged to the target level. We see an exponential increase of the timing at which the tipping point occurs as a function of θ ($R^2 = 0.956$, $F = 8{,}554.45$, $p < 0.001$, refer to Table S14 in the appendix for regression parameters). I believe the exponential increase in the timing of the tipping point can be explained by the "power law" structure of the network. Key players in the model are those ones holding positions that carry away other players with them. These positions are occupied by a few hubs in a preferential attachment model like ours, which makes these few hubs increasingly hard to tip with increases in θ; in contrast to a regular-structured network.

Figure 53b shows how the strength of the tipping point varies with θ. Essentially, higher adoption thresholds (θ) correspond to less pronounced tipping points. The figure illustrates the linear decrease in the strength of the tipping point with increases in θ ($R^2 = 0.888$, $F = 3{,}149.34$, $p < 0.001$, refer to Table S15 for regression parameters). I believe that the tipping in smaller chunks stems from the fact that higher barriers for particularly strongly restricted nodes will only be exceeded after re-running interventions several times before they are finally successful; which gives the adoption function a more cascaded curving (cf. Figure 52).

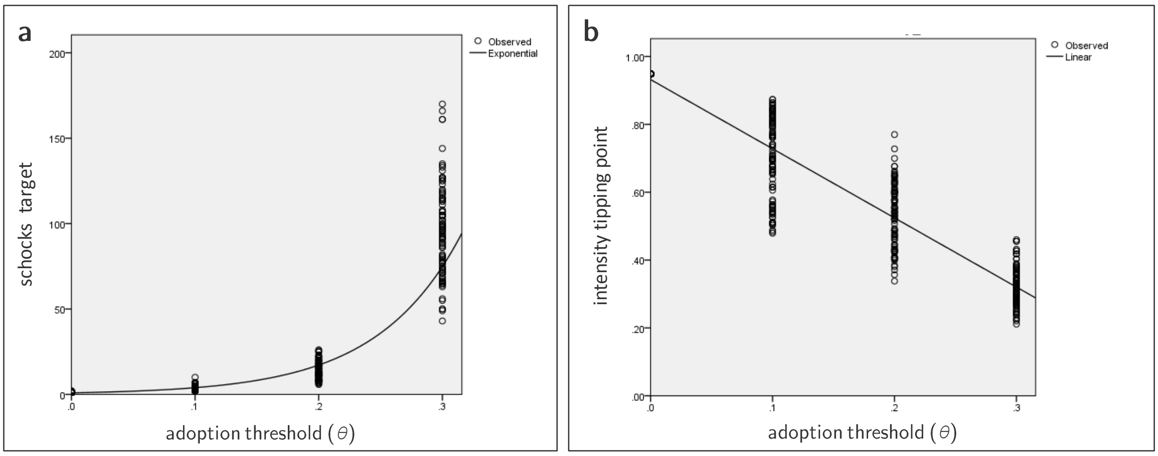

Figure 53. *Timing and strength of tipping point for varying thresholds (θ)*

To understand the adoption dynamics in more detail, I sliced the data in pieces and plotted the network at different points in time. Consider the series of plots for a low adoption threshold ($\theta = 0.3$) as shown in Figure 54. The timeline moves from the upper left to the right and then continues in the second row. The upper series of plots illustrates that peripheral airlines – weakly embedded in the network – adopt early (cf. Figure 54a). Initially, few core airlines switch to the new standard. The standard then gains ground slowly in the periphery as depicted in Figure 54b. Little happens over an extended time, which becomes obvious by contrasting Figure 54b and Figure 54c. Then, suddenly the standard breaks through as shown in Figure 54d. This is the brief moment when the network tips: almost all of the rest of the population herds to the new standard. Figure 54e and Figure 54f depict the contagion rounds directly subsequent to Figure 54d where more than half of the agents adopt. This is the tipping point, as shown in Figure 52, after which the system settles rapidly.

In summary, for low thresholds ($\theta < 0.3$) I find an *S*-shaped diffusion curve that is consistent with seminal diffusion models (Bass 1969; Rogers 1962). Individual thresholds determine whether a tipping point exists and non-innovation can be explained by the model as a function of individual thresholds. The timing of the tipping point increases exponentially with increases in the threshold and occurs in smaller chunks with increases in the threshold as a consequence of the network's "power law" structure.

Furthermore, I find a periphery-core effect whereby the new standard gains momentum in the less-restricted periphery and then spills over to the densely connected core. As lesser restrictions from the network structure may, however, be outweighed by the limited access of peripheral nodes to information, resources and competencies, further experiments will tap into non-random interventions that predominantly target central players in the densely connected core. Before I do so, I will enrich the model with size- and weight-adjusted thresholds that account for agent heterogeneity.

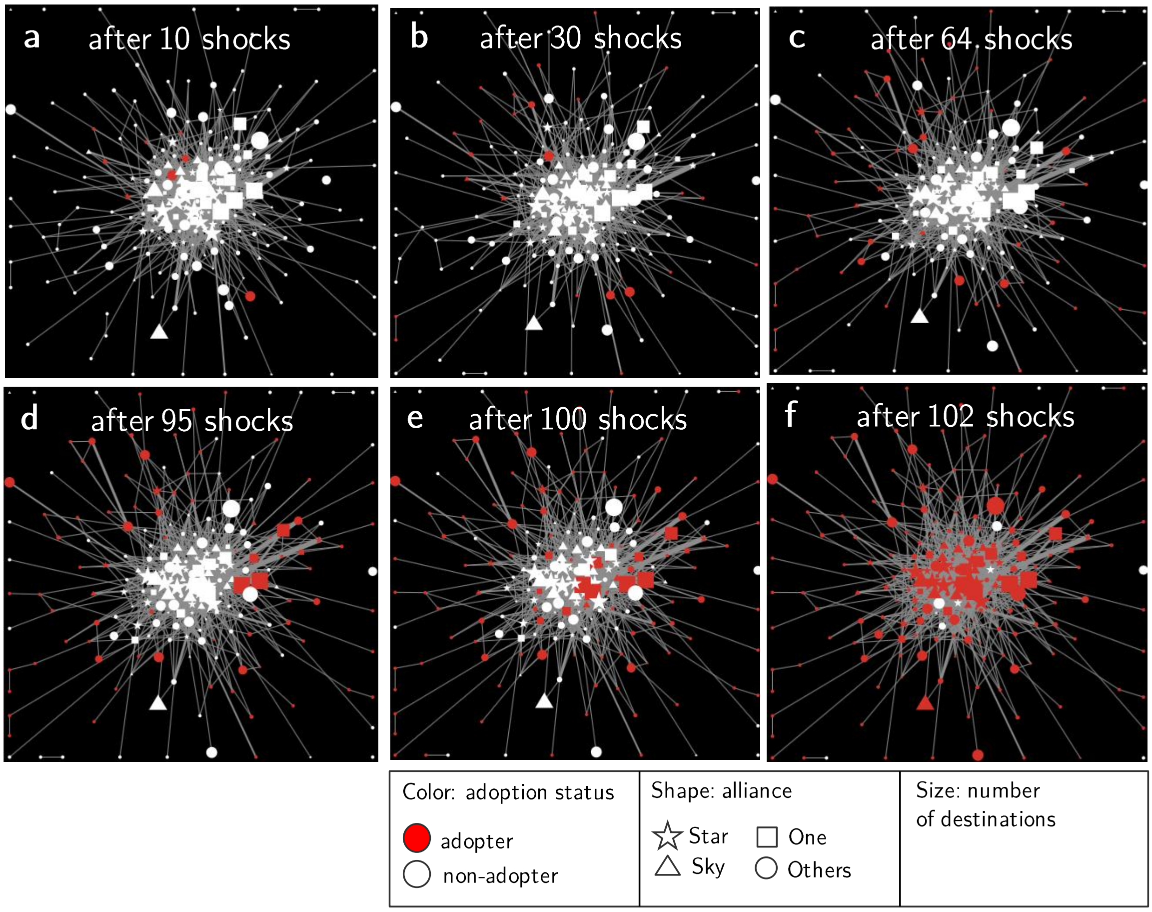

Figure 54. Adoption dynamics for one sample run in the codeshare network

This figure shows adoption dynamics for one sample run of the algorithm in the codeshare network for low thresholds (Θ = 0.3). The standard gains momentum in the periphery (figure a to c). The rapid spillover from a few to a large number of adopters (figure e to f) is clearly visible and occurs within a few periods. This is the tipping point towards the new standard. Refer also to movie oS2 in the online supplements.

8.3.3 Size-Adjusted Thresholds: Smallness Affects Alliances Differently

The next set of experiments examine to what extent agent heterogeneity, in the form of firms' sizes relative to their peers, alters adoption patterns. My data tracked 213 airlines and their size with regards to their number of served destinations. The carriers' size ranged from marginal ones with two destinations, to mega carriers with more than three-hundred.

Drawing on theorizing by Bothner (2003), I consider firm characteristics by adjusting individual organizations' thresholds with respect to size relative to their peers. Organizations small in size relative to their peers will be more adept at imitating their partners' strategies. Their individual threshold is rising. Larger organizations, relative to their peers, will in contrast be more resistant. Their individual threshold is adjusted upwards.

The mechanism, I envision, is one in which smaller organizations face less "structural" inertia to change their internal processes and systems (cf. Hannan and Freeman 1984) and are hence more willing to adopt the new standard. Recall that, in the growth model, I showed how inertia builds up as a function of new elements being added to a system. As a consequence, this adjustment links inertia on the organizational level conceptually with varying adoption thresholds among organizations on the industry level (refer to Figure 1).

Algorithm A.9 shows the procedure to size-adapt the agents' threshold. First, I rank each organization by size compared to their peers (line 2). I then compute each organization's (absolute) difference in positions by size to the median of all peers including the organization itself. Because size distributions were often skewed if there was one large organization in a group of peers, I chose to use the median instead of the mean. To derive at the adjustment factor, I compute an adjustment increment by dividing 1 by the number of organizations in the peer group (line 4). I further multiply the difference in positions with the increment to obtain the total adjustment factor (line 5). I then add the total adjustment to the threshold of the organization (line 6). This adjusts the adoption threshold upwards or downwards contingent on whether the organization positions above or below average in its peer group. By limiting the individual adoption threshold's upper boundary to one and its lower boundary to zero, I ensure that each adjustment results in a feasible solution (lines 7-8). Finally, it is checked whether the agent switches (lines 9-12).

Algorithm A.9	Size-adjusted threshold
1:	**foreach** agent *i* **do**
2:	rank order all agents $j_1,\ldots,j_n$ in neighborhood by the attribute size incl. agent *i*
3:	compute the agent's absolute difference in ranks to the median in the rank order
4:	increment := 1 / number of agents in the rank order
5:	adjustment := difference in ranks * increment
6:	threshold := threshold + adjustment
7:	**if** threshold > 1 **then** threshold := 1 **end if**
8:	**if** threshold < 0 **then** threshold := 0 **end if**
9:	**foreach** agent *j* in rank-order **do**
10:	**if** agent *j* has adopted standard **then** *adopted?* := 1 **else** *adopted?* := 0 **endif**
11:	**end foreach**
12:	**if** [sum] of *adopted?* $\forall$ agent $j_1,\ldots,j_n$ / count $j_1,\ldots,j_n \geq$ *threshold* **then** *switch* **endif**
13:	**end foreach**

Consider Air Berlin, a German carrier focusing on leisure and business customers. Based on the example, the mechanics work as follows: Figure 55a, on the left illustrates Air Berlin's position in its reference group of codeshare neighbors. The figure depicts each carrier's absolute number of destinations. Reverse coding Air Berlin's size in relation to its peers (cf. Figure 55a) shows that its size is above average. The airline occupies position thirteen of fifteen. As shown in Figure 55b, the carrier closest to the median is Etihad on position eight. Consequently, Air Berlin finds itself five positions above average in the rank order. Computing the increment as shown in Figure 55a arrives at a value of one-fifteenth. Hence, Air Berlin's threshold ($\theta_{Airberlin}$) is increased by one-fifteenth multiplied with five, which equals one-third. For any threshold, an extra of one-third of Air Berlin's peers have to adopt before the airline switches.

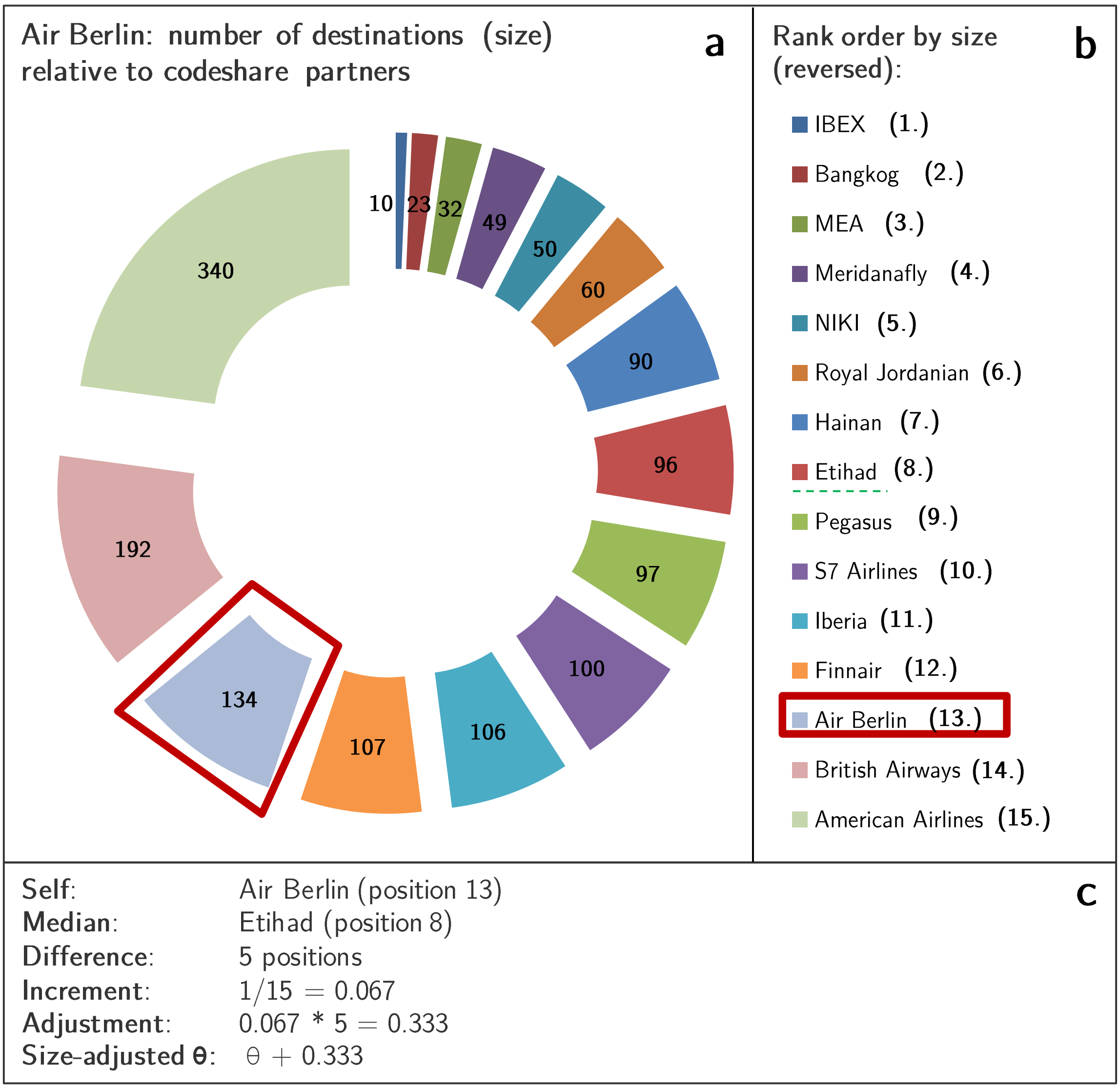

Figure 55. Example for the size-adjustment procedure for one airline

My starting point to investigate the effect of relative sizes is again the network of codesharing airlines. Varying the threshold levels (θ) in three increments, Figure 56 shows typical examples of how the proportion of switched airlines by size varies with θ. To construct this figure, I computed the fraction of adopters by size as the sum over the individual adopting airlines' sizes and divided it by the total size of all airlines in the network. One of the most salient features of Figure 56 is that the target level is exceeded for low *and* medium thresholds. Now, I observe herding to the new standard even for medium threshold levels ($\theta = 0.5$), in contrast to non-convergence in the simple model (cf. Figure 52). Because smaller airlines' individual threshold decreases, these airlines rush early to the new standard giving it a kick start. Because of this early advantage, contagions are easier to start. Early advantages for smaller airlines outweigh higher individual thresholds of larger airlines. Investigating the curving for a medium threshold ($\theta = 0.5$) in Figure 56, we see a step-wise increase in the proportion of adopters. Compared to Figure 52, the tipping point occurs in smaller chunks. The main finding from earlier simulations – that a tipping point exists for lower levels of θ – remains intact but agent heterogeneity shows that the tipping point occurs even for higher average thresholds. Tipping becomes dependent on airlines' sizes in addition to airlines' positioning in the codeshare network.

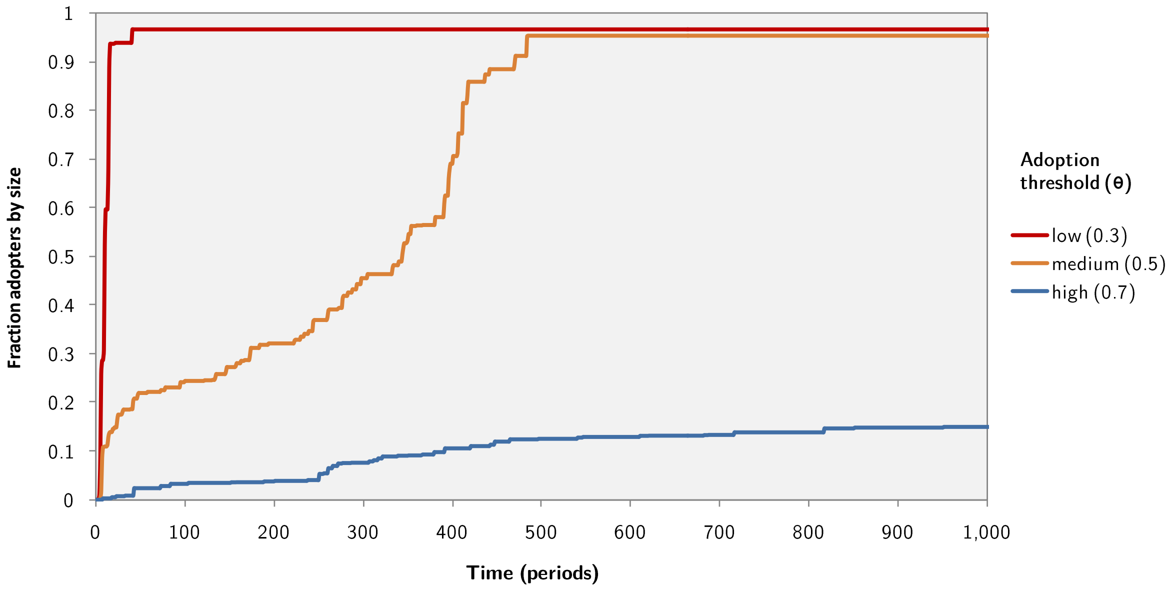

Figure 56. Adoption dynamics for varying levels of the size-adjusted threshold

Table 25 shows results for varying levels of θ. Consistent with Figure 56, we see that for low and medium levels of θ the system converges. As we continue to increase the threshold to levels above $\theta = 0.5$, the fraction of adopters falls as high thresholds now lower the chances that airlines switch. For high thresholds the system will not converge. My finding of an exponential increase in the timing of the tipping point as a function of θ was robust to the size-adjustment; however, slightly less variance could be explained by the model ($R^2 = 0.851$, $F = 3{,}989.09$, $p < 0.001$). The finding of a linear decrease in the intensity of the tipping point as a function of θ remained intact ($R^2 = 0.929$, $F = 9{,}110.67$, $p < 0.001$).

Table 25. Results for varying size-adjusted thresholds

	Adoption threshold[1,2,3] (θ)										
	0.0	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1.0**
Target Level?	yes	yes	yes	yes	yes	yes	yes	no	no	no	no
Adopters (%)	0.972	0.972	0.972	0.972	0.97	0.972	0.971	0.746	0.634	0.507	0.479
Std. dev.	0.000	0.000	0.000	0.000	0.00	0.000	0.004	0.000	0.000	0.000	0.000
$\text{Adopter}_{\text{size}}$(%)	0.986	0.986	0.986	0.986	0.98	0.986	0.985	0.487	0.358	0.254	0.235
Std. dev.	0.000	0.000	0.000	0.000	0.00	0.000	0.010	0.000	0.000	0.000	0.000
Timing TP	14.62	16.37	22.19	30.15	65.6	195.3	560.0	n/a	n/a	n/a	n/a
Std. dev.	3.926	4.303	6.919	7.526	19.8	47.21	101.8	n/a	n/a	n/a	n/a
Shocks targ.	3.230	3.480	4.430	5.990	12.2	36.53	105.4	n/a	n/a	n/a	n/a
Std. dev.	0.863	0.882	1.241	1.439	3.51	8.562	19.28	n/a	n/a	n/a	n/a
Intensity TP	0.640	0.562	0.454	0.330	0.21	0.113	0.066	0.047	0.036	0.030	0.028
Std. dev.	0.091	0.070	0.054	0.043	0.03	0.025	0.015	0.012	0.007	0.006	0.003

[1] Target level was 75% of the population and the simulation was terminated if this level was exceeded
[2] Average results for 100 simulation runs
[3] The time limit of the simulation was set to 7,500 ticks; *n/a* denotes non-converging cases

Consistent with theorizing by Bothner (2003), I expect smaller-sized organizations in the simulation to adopt earlier, as their individual thresholds (by assumption) became size-adjusted. I began my investigation of size-determinant adoption by implementing an additional measure that recorded, for a medium threshold ($\theta = 0.5$), the adoption events as a time series. I also further tracked the respective switchers' size. After clustering all 19,167 adoption events from 100 simulation runs by the sizes of the adopters, I was able to generate a table that displayed the average adoption period for each size-occurrence as one data point. Figure 57a shows the results. Before applying a regression model predicting the adoption point as a function of agent's size, I transformed the data by squaring the time of adoption (*noshocks*) to account for the strong clustering of the data in the bottom-left quadrant. Based on the transformed data, I could apply a linear regression model that found a significant relationship between size and the (squared) average adoption period ($R^2 = 0.516$, $F = 101.228$, $p < 0.001$, refer to Table S16 in the appendix for regression parameters).

In a next step, I examined whether organizations' degree (their number of codeshare linkages) predicts their time of adoption. Consistent with the observation by Granovetter (1985), I expect that organizations' that have a high degree will be more restricted by the network structure and will thus be less willing to adopt the new standard. Fixing the threshold to a medium level ($\theta = 0.5$), I again used a time series approach that tracked the time period of each organizations' adoption and their respective degree. Averaging results over 100 simulation runs, I generated a data set of organization's time of adoption and their degree. Figure 57b shows the results. Using a linear regression model, I found a significant positive link between organizations' degree and their adoption behavior ($R^2 = 0.492$, $F = 31.999$, $p < 0.001$, refer to Table S17 for regression parameters). The analysis provided preliminary evidence to suggest that high-degree airlines adopted at a later point in time than low-degree airlines.

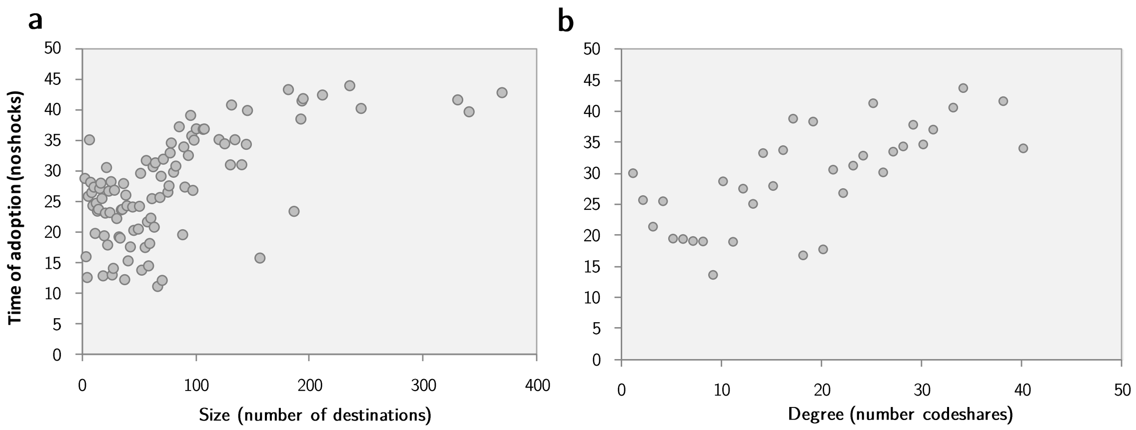

Figure 57. Average adoption period contingent on agents' size (a) and degree (b)

In a next step, I estimated how these effects vary across alliance and non-alliance members. Starting with the relationship between degree and time of adoption, I split the data in two groups and ran two regressions. The results suggest that the degree only predicts adoption times for alliance members ($R^2 = 0.325$, $F = 26.023$, $p < 0.001$, refer to Table S18 for regression parameters) while it fails to predict adoption times for non-alliance members ($R^2 = 0.005$, $F = 0.088$, $p = 0.770 > 0.05$, Table S18). Figure 58a and Figure 58b illustrate the differences quite clearly: while the relationship is strongly pronounced in the left-hand plot for alliance members (cf. Figure 58a) the effect vanishes for non-alliance members (cf. Figure 58b). Drawing on a t-test of regression coefficients, I could not, however, reject the null hypothesis that regression coefficients are equal across both groups ($t = 1.474$, $p = 0.145 > 0.05$).

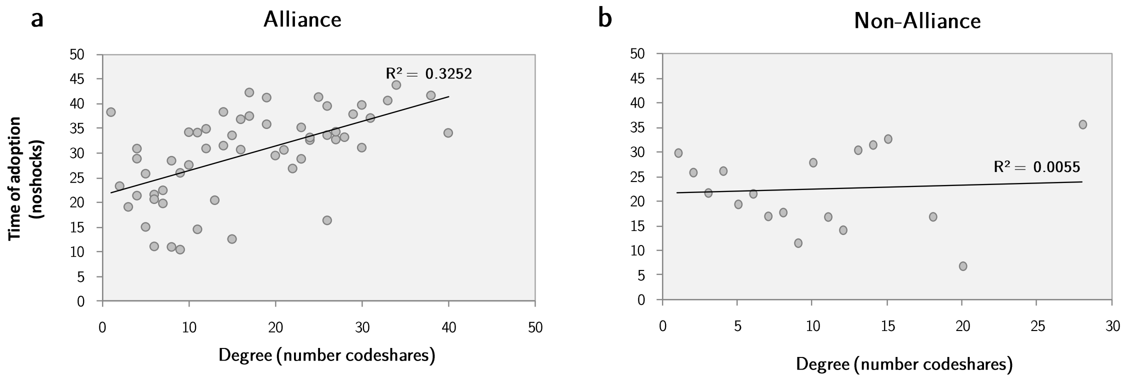

Figure 58. *Time of adoption by degree for alliance and non-alliance members*

This figure turns our attention to alliance membership as a predictor for an airline's time of adoption. In the figures I turn to the effect of airlines' degree: while there is a linear relationship for alliance members (figure a) where airlines that have lower degrees adopt earlier, there is no relationship between degree and adoption time for non-alliance members (figure b).

A similar effect can be observed for the relationship between size and adoption time: the relationship was pronounced for alliance members and correlation coefficients from a linear regression on the transformed data show a strong and significant relationship ($R^2 = 0.546$, $F = 85.449$, $p < 0.001$, refer to Table S19 for regression parameters), while no relationship could be observed for non-alliance members ($R^2 = 0.003$, F = 0.199, $p = 0.657 > 0.001$, cf. Table S19). Figure 58c and Figure 58d illustrate these inter-group differences quite clearly. In addition, the t-value was 9.244 and significant ($p < 0.003$), indicating that groups differ with respect to regression coefficients. Smaller airlines in alliances adopt earlier than larger airlines.

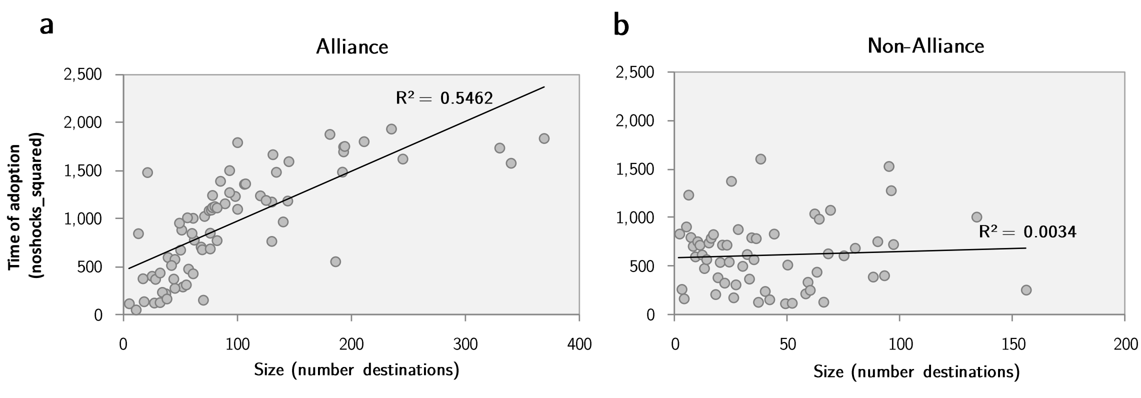

Figure 59. *Time of adoption by size for alliance and non-alliance members*

This set of outcomes is important because it suggests that taking into account group membership is a necessary part of understanding the link between organizations' importance (in terms of size and embeddedness) and their adoption behavior. Being small in an alliance may be usefully distinguished from being small in the others group. The next set of experiments will further illuminate the relationship between discerning factors of an organization's network embeddedness and adoption behavior.

8.3.4 Weight-Adjusted Thresholds: Strongly Tied Groups Will Not Adopt

In a next step, I account for link weights. Pursuing this objective is important because assuming that all collaborations are equally important could obscure the fact that some collaboration is significantly less intense than others. In distribution and pricing IT, advanced skills and substantial tacit knowledge are required to adapt and extend complex sales infrastructures that evolved over decades. Consistent with Hansen (1999) and Afuah (2013), I believe that influences in such knowledge-intensive settings will come from partners with which the focal organization has built trust from frequent and close relationships rather than from loose and marginal ones. I thus assume that partners with whom an organization has strong ties, will be more influential than marginal ones.

Two empirical examples back up my assumption. I interviewed RM experts from SWISS about which of their partners are most influential in determining their technology strategy in the area of distribution and pricing IT (refer esp. to interview oS13): most of the named partners, such as Lufthansa or Air Canada, were strongly coupled by existing codeshare linkages. Another example came up in an interview with another RM expert. The example concerns a transatlantic codeshare joint venture among SWISS and several other carriers. According to the interview (refer esp. to interview oS7 and observation memo oS16), SWISS had to reintroduce a conventional fare structure – with multiple fares per booking class – as several partners, with which SWISS thereafter collaborated intensively, could not support its advanced dynamic pricing approach that utilized only one or few fares per booking class. These examples illustrate the importance of taking into account collaboration intensities in computing the strength of peer influences.

Taking the number of codeshare routes among carriers as a starting point, I developed a procedure that penalizes less intensive collaboration. Figure 60 utilizes the example of SWISS to depict varying numbers of codeshare routes across different partners. In the figure, we see that a small fraction of partners, e.g. United, Lufthansa and US Airways, account for a substantial amount of all codeshare routes by SWISS. The example thus emphasizes my proposition on the importance of weighting peer influences according to different collaboration intensities. The example further illustrates the fact that drawing on the absolute number of codeshare routes could mischaracterize varying peer influences as marginal carriers would be grossly underrepresented and influences would only be exhibited by a very restricted group of peers. I thus restricted the weight-adjustment procedure to the rank order among an airline's peers as I suspected the stronger assumptions made by a cardinal procedure could over-represent intense partnerships while under-representing medium and small ones.

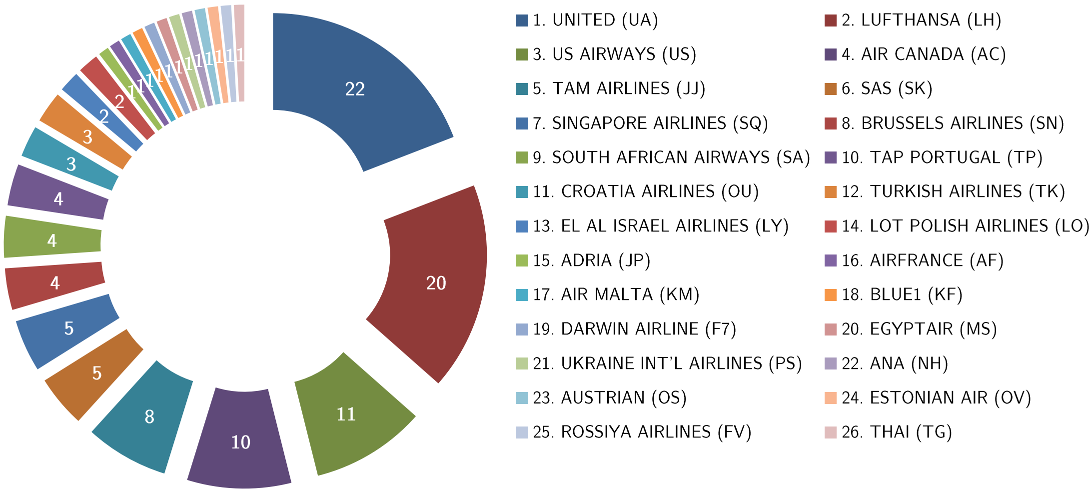

Figure 60. Example of the number of routes that SWISS codeshares with partners

Algorithm A.10 shows how I weight-adjust individual agents' thresholds, granting more weight for intense partners and penalizing non-intense collaborations. As shown in lines 2-3, I construct a rank order of all first-order neighbors of agent i and create an increment by dividing 1 by the number of peers. For each peer, I then compute a penalty according to the agent's position in the ranking (lines 4-9). Starting from the second rank, each subsequent position becomes penalized more strongly. As the penalizing procedure lowers the weight the agent's peers exert, Lines 10-11 balance the threshold accounting for removed overall penalty. Finally, the agent decides whether it should adopt according to the weight-adjusted threshold (lines 12-13).

Algorithm A.10 Weight-adjusted threshold

1: **foreach** agent i **do**
2: construct a rank-order of agents in reference group $j_1,\dots,j_n$ by collaboration intensity
3: increment := 1 / *number of agents in the rank-order*
4: **foreach** peer j in rank-order **do**
5: penalty := (rank in rank-order – 1) * *increment*
6: **if** j adopts new-standard **then** *adopted?* := 1 **else** *adopted?* := 0 **endif**
7: intensity-adjusted influence := (1 – *penalty*) * *adopted?*
8: **end foreach**
9: sum-penalties := Σ of *penalties* $\forall$ j in rank-order
10: balance-factor := sum-penalties / length rank-order
11: threshold := threshold * balance-factor
12: **if** Σ of *intensity-adjusted influence* $\forall$ j in rank-order / count agents in reference group $\geq$ *threshold* **then** *switch* **endif**
13: **end foreach**

Figure 61 turns our attention to adoption dynamics with respect to the weight- and size-adjusted threshold. We see a qualitative difference between situations with low or medium versus high thresholds. In the latter case, the system will not converge to the target level. A significant fraction of agents do not adopt the new standard.

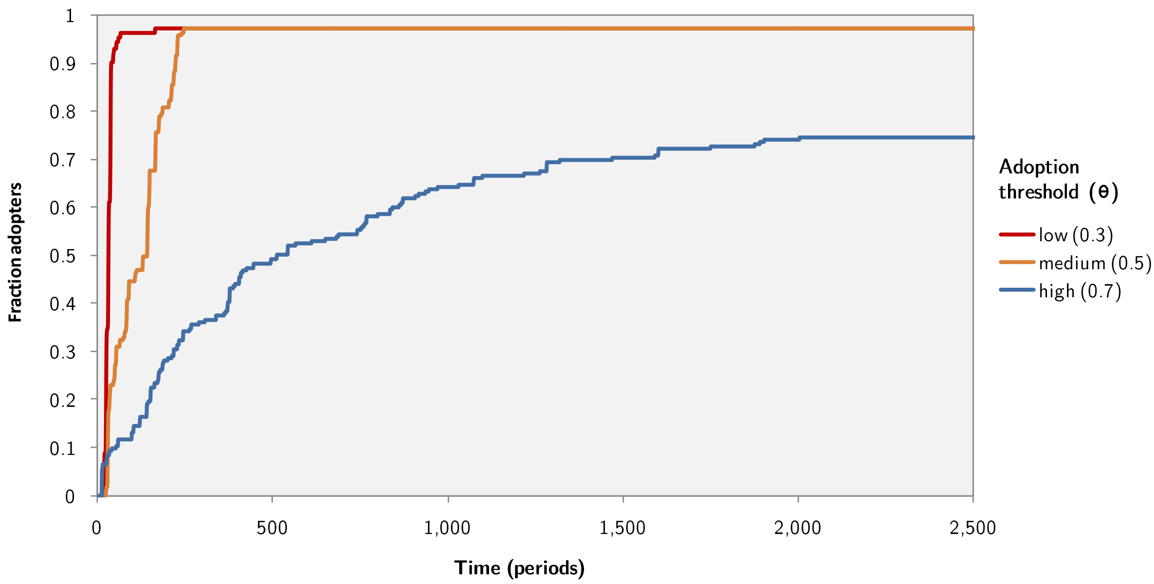

Figure 61. *Effects of weight- and size-adjusted threshold on the fraction of adopters*

Table 26 shows numerical results averaged over 100 simulation runs. We see that tipping occurs for low and medium thresholds. For high thresholds, the system comes close to the target level but failed to hit it in all cases. If weighted links are incorporated, some groups of agents will never adopt.

Table 26. *Results for varying weight-adjusted thresholds*

	Adoption threshold[1,2,3] (θ)					
	Low ($\theta = 0.3$)		**Medium ($\theta = 0.5$)**		**High ($\theta = 0.7$)**	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Target level?	yes		yes		no	
Fraction adopters (%)	0.972	0.001	0.972	0.000	0.746	0.000
Size adopters (%)	0.986	0.000	0.986	0.000	0.487	0.000
Timing tipping point	29.250	7.259	198.790	41.969	n/a	
Shocks target	5.850	1.410	37.120	7.566	n/a	
Intensity tipping point	0.334	0.044	0.107	0.021	0.049	0.012

[1] Target level was 75% of the population and the simulation was terminated if this level was exceeded
[2] Average results for 100 simulation runs
[3] The time limit of the simulation was set to 7,500 periods; *n/a* denotes cases non-converging cases

Consider in this connection the series of plots in Figure 62. The main insight that emerges from these figures is that whether a clique or group adopts, depends on the linkage structure among neighboring agents. In Figure 62a, I depicted two nodes, large in size and strongly connected, with weak ties to other nodes. The influence from the other agents may not suffice to tip either of these two large nodes. In Figure 62b, I adapted the linkage structure only marginally. I rewired one of the other agents, resulting in a situation in which all the outside influence concerns one of the large players. In contrast to the previous example, outside influences may now exceed the threshold level and the agent switches. This switch immediately results in a subsequent switch of the other large player, too.

The individual linkage structure is therefore decisive for whether – given the same level of influence – one group of connected agents can counterbalance strong ties between other groups of agents.

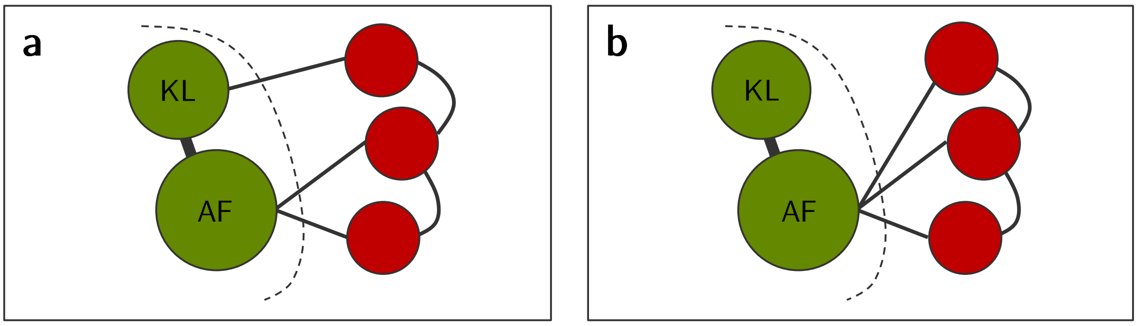

Figure 62. Influence of interaction structure on adoption behavior of groups

8.3.5 Targeted Interventions: Collective Action by Maximum Cliques

The next set of experiments moves away from random interventions to more purposeful ones. One may think of a collective action by a group of willing airlines or by an arbitrary strategic alliance (cf. Botzem and Dobusch 2012; Brunsson et al. 2012). Random interventions assume that innovations occur with equal probabilities in any part of the network. In core-periphery structures, as found for airline codeshares, core members may, however, find it more useful to join forces to move collectively to the new standard; in turn, isolated airlines may be less likely to adopt modern practices and methods (cf. Valente 1995; Valente 2012).

I pursue the objective to test empirically two theoretical propositions: first, I want to examine whether targeted network interventions can outperform random interventions (Valente 2012). Targeted interventions are those interventions identifying sets of key players purposefully that are expected to maximize the diffusion outcome (Borgatti 2006). Consistent with the observations by Valente (2012), I expect that targeted interventions on a segment-level are most effective if they utilize group detection algorithms as important groups of players may find it difficult to adopt "unless the entire group agrees to use the system at the same time" (Valente 2012:337). Hence, I propose that targeted interventions, utilizing group detection algorithms, can outperform random ones. The null hypothesis is that both strategies perform equally (or targeted interventions perform even worse). Second, I want to tap into the extent to which targeted network interventions can be more resource-effective in reaching the goal of maximizing diffusion outcomes than "coalition-building by convenience". By selecting sets of key players purposefully with the goal of maximizing diffusion outcomes, I expect that the model can outperform interventions that draw on a random attribute of group membership that evolved in another context or targeted another objective. Thus, one may be able to focus resources on sets of key players that are relevant for the given problem at hand (with respect to the number of players that have to be triggered in the first place). Alliances are a good example.

I thus compare the group detection algorithm with the switch of an entire alliance. I used Star Alliance as a test balloon as it is the largest alliance in the codeshare network by the number of members and affiliates.

Many different approaches have been proposed for group detection (cf. Palla et al. 2005; Fortunato 2010; Valente 2012). These range from traditional techniques such as hierarchical clustering, modularity-based methods, and methods based on statistical inferences, to methods for overlapping communities (Fortunato 2010). Technically, the problem of clique detection has basically been defined as detecting complete subgraphs ("cliques"), i.e. sets of nodes where each pair of nodes is linked. In a social network, one may think of cliques as subsets of people that all know each other. The *maximum clique* then designates the largest subset of nodes being completely connected (Fortunato 2010). To test my proposition regarding different intervention strategies, I draw on the *Bron–Kerboscht algorithm* (Bron and Kerboscht 1973) as it is a well-known and efficient algorithm to detect cliques in networks. The basic form of the algorithm is a recursive backtracking that searches for all maximal cliques in a given graph G. The algorithm augments a candidate clique by considering one node at a time, either adding it to the candidate clique or to a set of excluded nodes that can't be in the clique but must have a number of non-neighbor in the final clique (cf. Bron and Kerboscht 1973). The result is a vector of nodes (airlines) designating a maximum clique. In the codeshare network, the maximum clique consisted of eight members (4% of the population); Lufthansa (LH), United Airways (UA), Swiss (LX), Thai (TG), and Air Canada (AC) among others.

To test whether interventions to the maximum clique outperform random interventions, I pick the same number of nodes as the maximum clique size uniformly at random. Overall, I thus proceed with three intervention strategies:

1. *Random-nof*: A group of players of the same size as the maximum clique
2. *Max-clique*: The set of key players that belongs to one of the maximum cliques
3. *Star*: Star Alliance members (all nodes holding this attribute)

To test the theoretical propositions, I adjust the experimental design; in the following, I perform only one shock to a set of players (a block, clique, cluster, or random set of nodes) to examine the extent to which their collective action affects the new standard's diffusion in the overall network. Consequently, I extend the triggering event from one random node to a set (or list) of nodes that I input either at random, purposefully, or as a result of a group detection algorithm. Then, I investigate a single round of contagions (one cascade or shock). I investigate whether the shock is sufficient to tip the overall network to the target level. This time, it is assumed that coalitions will stay with the standard once they have adopted. Varying the adoption threshold θ in three steps (low, medium, high) for the three intervention strategies (*random-nof*, *max-cliques*, *star*), I conducted 3 x 3 x 100, equals 900 experiments. I utilized the weight-/size-adjusted threshold θ, developed over the previous sections. In addition, I performed experiments for the complete interval of thresholds, $\theta \in [0,1]$, in increments of 0.1. The complete set of results can be found in the supplementary materials in Table S20.

Focusing on the maximum clique strategy, Figure 63 shows the adoption dynamics for a typical run of the simulation for a low threshold ($\theta = 0.5$). As shown in Figure 63a, we see quite clearly that the maximum clique is situated within the core of the network and that most members belong to Star Alliance (indicated by the Star-type shape); they are mostly large in size (the size of each node indicates its number of destinations). In the first contagion round, the standard spills over from the maximum clique most intensively to a large number of adjacent nodes (cf. Figure 63b). The second contagion round mostly spreads the standard further to the periphery (cf. Figure 63c) but the large wave already slows down. The third, fourth, and fifth contagion round contribute only marginally to the new standards diffusion.

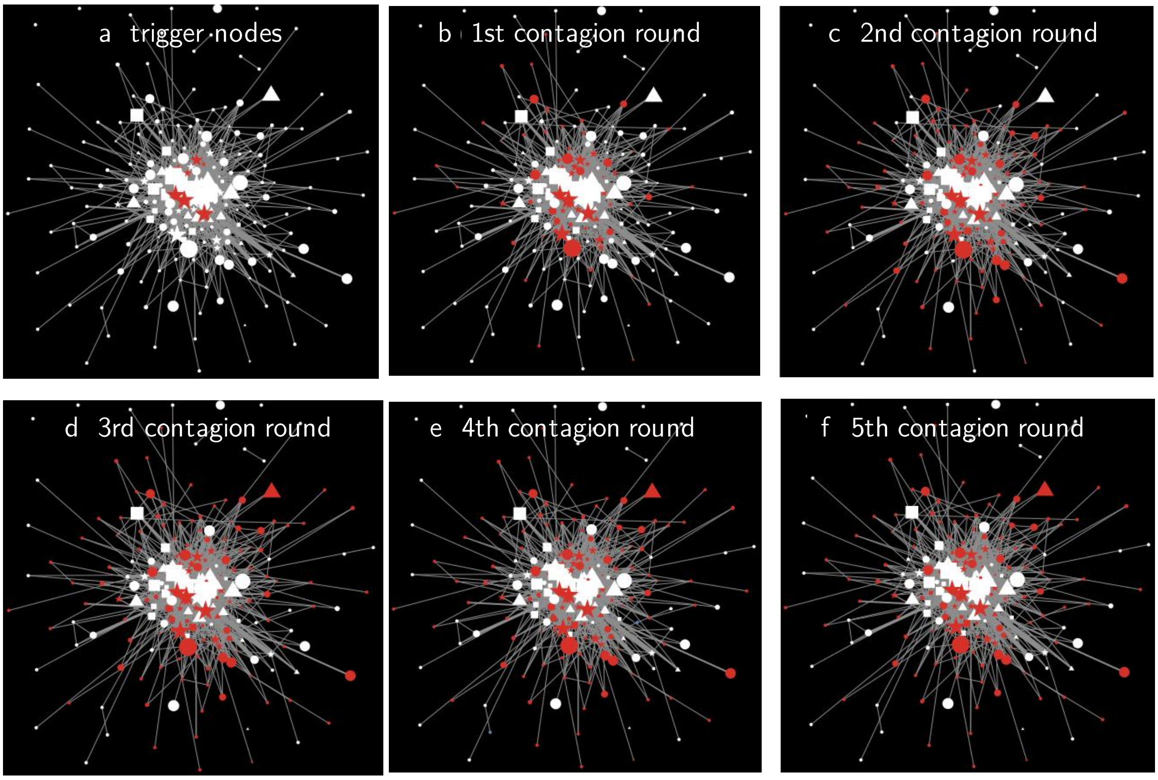

Figure 63. Adoption dynamics for maximum clique strategy in one sample run

This figure shows how adoption dynamics unfold within the frame of the maximum clique strategy for a low threshold (θ = 0.3); cf. movie oS3 in the online supplements.

Figure 64 shows how different intervention strategies (*random-nof*, *max-clique* and *star*) affect the proportion of adopters after one cascade. When the threshold is low ($\theta = 0.3$), the *max-clique* strategy performs well above the *random-nof strategy* and almost reaches the target level of 75%.

The *max-clique strategy* also delivers comparable results to the *star strategy*. We see substantial cascades from few members of the population. For medium thresholds ($\theta = 0.5$), the extent of cascades falls for each of the intervention strategies below the target level. Both *random-nof* and *max-clique strategies* suffer extensively while the *star strategy* is surprisingly robust. For high thresholds ($\theta = 0.7$), *random-nof* and the *max-clique strategy* again suffer substantially while the *star strategy*, again, faces only a little decline.

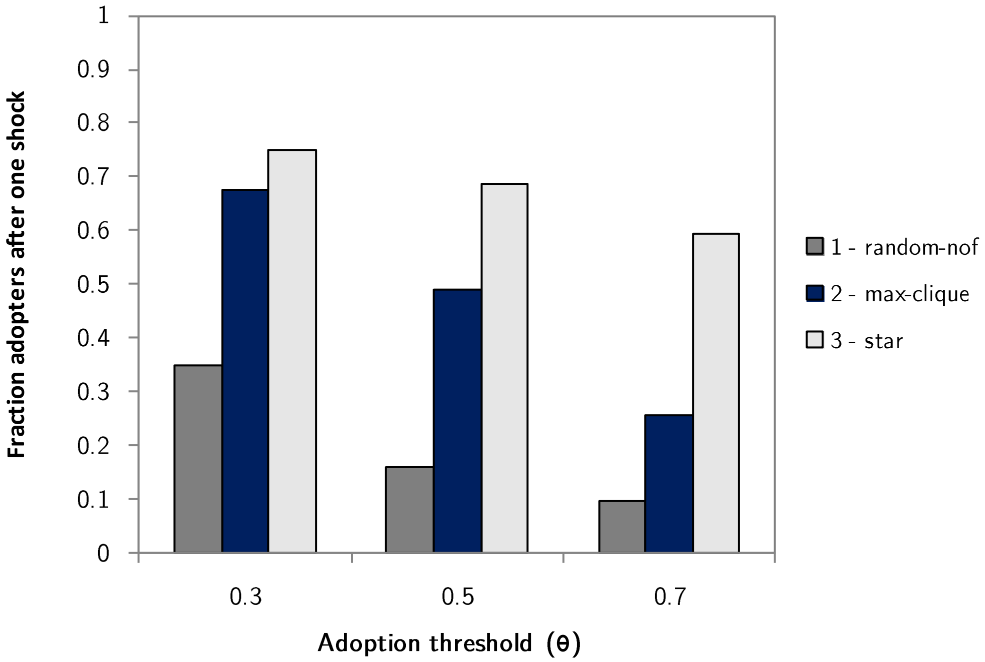

Figure 64. Fraction of adopters after one shock for different intervention strategies

As a next step, I examine whether targeted interventions can outperform random interventions. The averaged data in Figure 64 offers a valuable initial vantage point. Limiting our attention to cross-group differences between random interventions (*random-nof*) and group detection (*max-clique*), I used an ANOVA to test the significance and the strength of the effect. Table 27 shows the results. I find significant differences in group means for each examined threshold level ($p < 0.001 \ \forall \ \theta$) and strong effect strengths (η^2). These results build confidence in my theoretical proposition that targeted interventions can outperform random interventions.

Table 27. Across-group difference for random interventions and max-clique strategy

Threshold	Strategy	Mean[1,2]	Std. dev.	F	p	η^2
Low ($\theta = 0.3$)	1 – random-nof	0.347	0.116	722.102	0.000	0.785
	2 – max-clique	0.677	0.038			
Medium ($\theta = 0.5$)	1 – random-nof	0.157	0.061	1381.944	0.000	0.875
	2 – max-clique	0.488	0.065			
High ($\theta = 0.7$)	1 – random-nof	0.096	0.037	1405.192	0.000	0.876
	2 – max-clique	0.256	0.021			

[1] Dependent variable was fraction of adopters after one shock
[2] Average results for 100 simulation runs

As the switch of an entire alliance (*star strategy*), for each threshold, outperformed targeted network interventions (*max-clique strategy*), I had to reject my second hypothesis that group detection is able to reach the same level of adopters as "coalition building by convenience".

Figure 65 shows how cascades differ between the max-clique and the star strategy. We see that both strategies start from a different level – the *max-clique strategy* targeted 8 members (4% of the population) while the *star strategy* targeted 34 members (16% of the population). The subsequent cascades peak stronger for the *star strategy* but then run dry very fast. To some extent, this can be explained by the fact that the large numbers of targeted nodes have direct paths to a larger number of adjacent nodes. The *max-clique strategy* shows an interesting dynamic. For low thresholds ($\theta = 0.3$), the first and second round of contagions will switch almost the same number of nodes. At that level, the *max-clique strategy* performed almost equally to the star strategy. For medium and high thresholds, there is however a strong or even very strong decline in the extent of the cascade after the first contagion round.

In summary, for low thresholds (θ = 0.3), I found that both strategies yielded similar results. For medium and high thresholds (θ = 0.5 and θ = 0.7), however, I observed a significant drop in the effectiveness of the *max-clique strategy*. Viewed together, these results suggest that group detection strategies may not be equally effective across settings, and that not only "understanding who is part of the core is critical for the coalition success" (Valente 2012:49) but also how individual actors incentive structures vary.

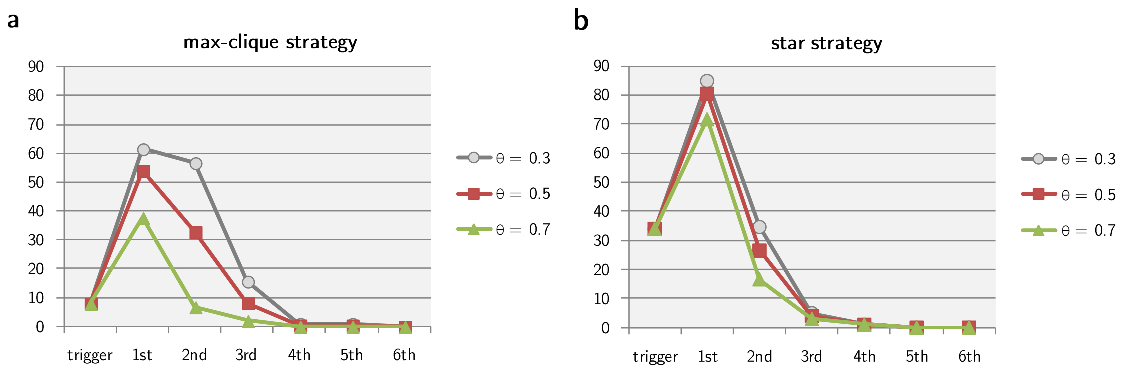

Figure 65. Adoption dynamics over one cascade for max-clique and star strategy

This figure shows the adoption dynamics within one cascade after an intervention that targeted (a) a maximum clique, and (b) all members of Star Alliance. The figure plots the absolute number of adopters in each contagion round for varying thresholds (θ)

I performed additional experiments using a brute force method in which I first created a large number of combinations at random (i.e. sets of 10,000 or 100,000) from all possible combinations[20] and then tested all of these seeds for their effect on the fraction of switched agents. I included results for the two best-performing seeds in the supplementary material Table S21. While these strategies outperformed random strategies, the search did not find a seed that was able to beat the maximum clique strategy.

[20] Consider, for instance, a situation in which 213 agents ought to be placed on 8 positions (8, because this is the number of agents in the maximum clique). Then, there are $C = M! / ((M - N)! * N!) = 213! / ((213 - 8)! * 8!) = 9.19906903e13$ possible combinations.

8.4 Discussion and Preliminary Conclusion

8.4.1 Interpretation

This contribution was aimed at understanding tipping points for the diffusion of a new distribution standard in the airline industry. To briefly summarize, I constructed a data set of codeshare linkages among airlines and performed a network analysis. The presented contagion model then shocked particular agents uniformly at random. This intervention triggers cascades running through the network. Based on peer influences, the algorithm assesses whether agents switch to the new standard. Agents adopt if individual level thresholds are exceeded.

Utilizing the codeshare network to assess different scenarios, I found that whether a tipping point exists depends on individual level thresholds. Essentially, for low thresholds, the functional relationship between the fractions of switched agents over time shows an S-shaped form (cf. Figure 52) replicating findings from seminal models of innovation diffusion (cf. Rogers 1962; Bass 1969). As a notable extension to previous attempts, my approach also enables for explaining of innovations' non-spread; this is a theoretical step forward towards understanding diffusion processes' micro foundations (cf. Kiesling et al. 2011).

While the standard diffused to a nontrivial fraction of airlines for low average thresholds, cascades ran dry for medium and high average thresholds (cf. Figure 52). In addition, convergence time grows exponentially with increases in the threshold level (cf. Figure 53a). This result is important because it suggests that the network structure is important for the diffusion of a new standard. It particularly shows that, in a network with a "power law" structure, the diffusion of a new standard may be very sensitive to changes in adoption thresholds. More broadly, it also highlights that even a small decrease in the threshold – for instance as a result of minor technological advancements – can significantly increase the probabilities that a new standard diffuses. Interviews, for instance, suggest that progress in the area of fare quote engines – converting fare quotes from GDS to a company's dynamic pricing engine – may be such a central piece of the puzzle that could spur up overall adoption significantly (refer to RM experts in interview oS11).

I then highlighted the importance of agent heterogeneity as a factor that facilitates or impedes standard diffusion. Extending the model by Bothner's (2003) observation that small firms are often more likely to copy their peers' technology strategies, I size-adjusted the agents' adoption thresholds relative to their peers. Performing experiments for varying thresholds, I found that the average threshold, for which the predefined target level was exceeded, decreased in a heterogeneous setting compared to a setting with simple thresholds. Consider the different diffusion curves for medium thresholds in Figure 52 and Figure 56: in the size-adjusted model, the new standard gains momentum even for medium thresholds. I believe this result aptly captures the emergent effects that can arise when the early tipping of the most-adaptable group lowers the overall threshold at which a tipping occurs.

Additional analysis on the effect of size and degree on the time of adoption revealed an interesting distinction: being small in size and degree mattered most in an alliance context.

I found that a significant relationship between an agent's degree and size and the time of the adoption could only be observed for agents that belong to any of the three alliances (cf. Figure 58a and Figure 59a). For non-alliance members, the effect was absent (cf. Figure 58b and Figure 59b). This result is substantially important because it indicates that being small in an alliance can mean something entirely different to being small in another group. It also suggests that targeted network interventions focusing on agent characteristics and centrality may not be equally effective across different groups of agents.

Investigating the adoption dynamics in the model in detail revealed that the new standard grows in the periphery as agents close to the periphery are less restricted by prevailing network effects (cf. Figure 54). The standard may then spill over to the densely connected agents in the core. However, significant numbers of shocks were necessary until the new standard spilled over. Viewed from an organizational perspective, I suspect that peripheral players will often lack resources, competencies and knowledge to adopt early. Furthermore, core players may be more willing to adopt early as they face stronger competitive pressure and are thus more adapt to explore an innovation that potentially enables them to gain a competitive advantage. Due to their restricted network position, they may thus build coalitions to move collectively to the new standard. To illuminate the consequences of collective efforts, I turned my attention to non-random interventions triggering events that shocked multiple players at once, tracking the effect on the overall network. Suggesting an algorithm for community detection in graphs, I conceptualized collective action as a situation in which the largest clique in the network switches collectively. I focused on the one-off effect of this local action on the global diffusion outcome. Comparing this intervention strategy with random interventions and the move of all members of an arbitrary alliance, I found that community detection could outperform random interventions and performed close to more resource-intensive collective actions by an entire alliance – at least for low and medium thresholds.

8.4.2 Limitations: Beyond Either-Or, Undirected Links, and Static Networks

Before sketching future directions and implications for other lines of research on the diffusion of standards and innovations, I emphasize three conditions that limit the generality of the perspective I have presented.

Firstly, there are clearly settings in which organizations are not restricted to either adopting or non-adopting a new standard and where an *as-well-as* logic – in which multiple standards co-exist over extended periods – therefore defines the network. Consistent with the observations by Hanseth (2000, 2002), and Monteiro et al. (2013), I believe that standardization is a complex process occurring on multiple levels of an information infrastructure at several, discontinued points in time. Consider in this connection the multi-level analysis of SWISS in Figure 45 and Figure 46 whereby the first figure represented SWISS' embeddedness in a network of codesharing carriers and the latter figure drilled down to SWISS' network of information systems. One can clearly see similarities between both figures as codesharing also has a technical aspect, integrating inventory systems from multiple partnering carriers; there are, however, aspects that are abstracted away by assuming that an airline either adopts or not. In connection to that point, Hanseth (2002) emphasizes the importance of gateways for the success of creating new paths. I believe that the example of SWISS shows the essential need for conversion technologies as – when adopting a new standard – organizations have only limited capacities that require keeping some domains fixed, at least preliminarily (cf. Schreyögg and Sydow 2010). Future work could give a more fine-grained account for varying abilities to implement a new standard. A starting point would be to link my growth model with the perspective presented in this chapter.

Secondly, I considered codeshare linkages as undirected. There are clearly settings in which peer influences are unequally distributed among both partners in a mutual codeshare relationship. One may think of the example of SWISS and Lufthansa as shown in Figure 45. While both carriers codeshare intensively, peer influences may not weigh equally strongly for both partners. In the example, SWISS is part of the Lufthansa Group, which not only provides financial backup but also implements measures of managerial control that may imbalance both partners' influences on each other. I believe that my approach already covered important aspects with respect to partnership-specific power imbalances by feeding back a carrier's size relative to their peers into agent's decision making. In settings where one partner is large and the other partner is small, the larger carrier's adoption threshold is adjusted upwards while the small carrier's adoption threshold is adjusted downwards. My approach may, however, mischaracterize situations in which peer influences are unequally distributed despite equal sizes of both carriers. In addition, it is also possible to imagine situations in which the smaller partner dominates the larger partner in terms of technology strategies. As information on the directions of influence are impossible to infer from public codeshare data, a valuable initial vantage point for recasting my approach could be to complement the codeshare matrix $\boldsymbol{A}$ by a matrix of financial linkages $\boldsymbol{B}$. As suggested by Elliott et al. (2014), such modeling could account for the direction and intensity of financial linkages among organizations. As suggested by Greve and Seidel (2014), one could also enrich my approach by using regional proximity as another measure in a net of multiplex influences.

Thirdly, while I have aimed to accurately characterize important dynamics on the target under investigation to distill stylized facts while preserving the simplicity of the model, it may be entirely plausible that the new standard takes an entirely different trajectory to the ones projected in the model. As the NDC standard is in its early stage of business adoption, it remains open which trajectory the standard will eventually take and whether the outcomes will match the model. My research aims to gain original insight into potential scenarios with respect to the diffusion of a new standard and is hence not intended to predict a particular trajectory. To gain face validity, I discussed my findings carefully with domain experts of a case company, industry stakeholders and other researchers. There are, however, possibilities that dynamics outside the model rule out scenarios that have been found as useful or instructive. Unfortunately I cannot fast forward the tape of history to see how the new standard unfolds. I thus emphasize the need to replicate the model in other settings to see whether the particular trajectory that the standard diffusion process eventually took can be sampled from the universe of parameter combinations incorporated in the model.

8.4.3 Future Directions: Market Structure, Effective Interventions, and Dynamics

In addition to applying the model to other settings, especially those in which standardization has already taken place and standard diffusion outcomes are therefore straightforward to replicate, I present four particularly promising ways to proceed further.

Firstly, although the codeshare network – and the model that I build thereupon – enables us to draw a quite detailed picture of how airline interactions affect individual level standard adoption, it is easy to imagine a more complex model taking into account a multi-tier market structure with GDS, Internet aggregators and other stakeholders. The airline-specific industry structure with GDS as a problematic broker is essential to understanding why there are problems switching to a new distribution standard. To this end, Figure 66 points to the particularities of the airline industry with respect to the market structure creating problems when switching to a new standard. A short history of the GDS evolution reveals the strong impact that these systems have on current inertial tendencies in airline distribution and pricing. GDS have evolved since the 1960's from airline reservation systems (Copeland and McKenney 1988). Later, when regulatory concerns in the US and Europe were raised, GDS were spun off from airline companies (Belobaba et al. 2009; Copeland and McKenney 1988). Tendencies towards oligopoly in the market for platforms for commercial and technical cooperation have been strongly promoted by increasing returns in the two-sided market of travel agents and transport companies. This operationalizes in a straightforward positive feedback spiral that is contained in material I received from GDS vendor Amadeus (refer to Figure S2): the more routes and connections become available in a travel platform, the higher the value for a transport company to bring additional content to a travel platform, the higher the value for travel agents to use these platforms for their bookings, which in turn reinforces the value of the platform to the airline. This is a network effect that leads to increasing returns until the entire inventory of a particular carrier is utilized and outweighs competition in the platform with other transport companies as the other option – non-presence in the travel platform – results in the loss of profit. Interviews showed that this is almost a non-option for airlines as they face a strongly competitive market environment in which they drive close (or even below) profitability (refer to RM expert in oS2). This goes together with an indirect network effect which is due to the fact that abnormal returns for GDS could be re-invested into platform enhancements; more transport companies also bring complementary services and products (e.g. car rental, hotel rooms) to the platform which further increases the value of the platform. Furthermore, GDS could use high returns to expand into complementary areas such as airline distribution IT, which further strengthens the "consumer lock-in" (cf. Greenstein 1997). Amadeus, for instance, earned in 2012 a return of 1,108 million Euro (Earnings before interest, taxes, and depreciation; EBITDA) giving revenue of 2,900 million Euro (refer to oS23). While this story may be told as a problem of the economics of IS, one could also focus more explicitly on the technical dimension of GDS infrastructures. GDS operate enormous information infrastructures going beyond even the largest organizational IT infrastructures. Amadeus, for instance, operates a data center in Erding, Germany, processing more than 1.6+ billion transactions and 3.7+ million net bookings per day (on average days in 2012; refer to oS26). This is beyond any imagination and adds a concrete technical dimension to these economic figures. Distribution standards such as the passenger name record and booking classes are deeply embedded in these infrastructures. Several interviewees reinforced my impression that attempts to reengineer the GDS go beyond the capacities of any of the GDS vendors. This is substantiated by the following expert statements:

> *“So there is an enormous amount of fundamental logic locked up in those GDSs that is, no one knows, what is there. It would, what it takes to change something is extremely costly and the people who originally, most of this is undocumented and the original writers and even the second generation of people who worked with it, are mostly dead.*” (revenue management expert; refer to interview oS17)

> „*This is such a fundamental part of this entire software, yes. If you had switched this concept, you could not have done that [...] would had not been technically feasible; absolutely right. Not technically feasible.*“ (GDS manager and distribution IT expert; refer to interview oS20)

This is illuminating for the underlying reasons for diverging interests between GDS vendors and airlines with respect to the booking class standard. As GDS are also in wide use across car rentals, hotels, cruises, railway companies and further industries (Farhoomand 2000), this creates additional barrier to change (GDS manager and distribution IT expert; refer to interview oS20).

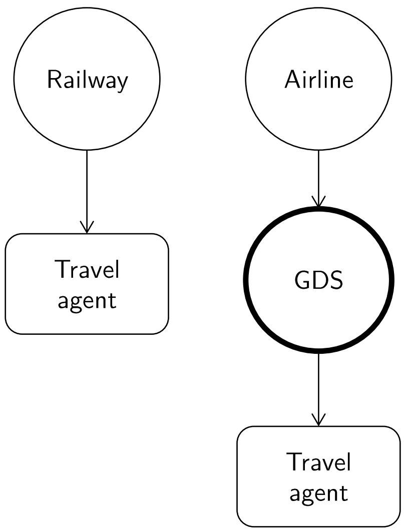

Figure 66. Airline-specific industry structure. GDS as a problematic broker

Extending my model in this direction would require modeling these actors as additional agents, specifying their group-internal interactions and their interactions with airlines as well as equipping them with realistic adoption thresholds. Figure S8 in the appendix is a first step into this direction. I believe this figure is important as it sketches centrally the multiplicity of interactions between airlines, GDS, and aggregators. Consistent with Hanseth (2002), the figure therefore reemphasizes the importance of considering converters between the established booking class standard and a potential new airline distribution standard; it especially portrays the need for airlines to remain compatible with the GDS as they are an indispensable source of revenues now and for the near to mid-term future (refer to RM experts in oS2 and oS7). Due to the particularities of airline distribution IT, with its increasing return nature from combining offers in large platforms, I believe it is necessary to recast the model to account for this important structure; a useful starting point could be the Modified Polya Process – shown in Figure 8 – as it is able to capture the complementarities that arise from the interactions between airline-internal systems and aggregators' infrastructures. However, the Modified Polya approach would need, again, recasting with respect to interaction patterns.

Secondly, I emphasized the importance of non-random intervention strategies – especially those utilizing a maximum clique strategy for group detection – to ensure the rapid and effective diffusion of the new standard. Targeted network interventions are a fruitful yet underexplored research area (Valente 2012). Examples in this area are Borgatti's (2006) algorithms to find sets of key players that maximize diffusion outcomes or actor centrality-based approaches as suggested by Ballester et al. (2006) or Jackson (2008b). Taking into account the modular structure of my model, other, non-random invention strategies can be plugged into the model easily to test whether these strategies are able to perform similar or even outperform the maximum clique strategy I have presented as the backdrop of my approach. Future research could also build upon the counter-intuitive, brute force approach that I have sketched (refer to the results in appendix Table S21); such an approach would be especially helpful to find key players that maximize the diffusion outcomes while minimizing the resources with regards to the number of players that have to be mobilized in the first place. Rerunning the model multiple times for each possible combination is, however, computationally costly. A more feasible approach could thus be to use a genetic algorithm or some other heuristic to find sets of key players from the large number of all possible combinations that satisfy a predefined outcome measure with respect to diffusion outcomes and costs more effectively. This presents interesting challenges for future research.

Thirdly, I assumed a fixed underlying transmission network, designated by the codeshare matrix $\boldsymbol{A}$ as well as fixed agent attributes (i.e. size and alliance membership). In turbulent environments, this assumption may be too restrictive. My work on growing networks (refer to chapter 4-6), was motivated particularly by the observation that airlines enter and drop out of networks regularly. For instance, with a rate of 15.9% yearly for Star Alliance. Furthermore, I had to cleanse the data as 18 (of 231) carriers ceased operations from 2011 to 2013. In addition, new codeshares are announced on a weekly or monthly base creating further dynamics. IATA assumes that business adoption of the new standard will require at least three years. Recasting the model to account for these dynamics may extend the approach accounting for growth (refer to Algorithm A.3) and dropout processes (Algorithm A.7) on the individual node level as well as matching this data with empirical observations on the timing and intensity with which new codeshares emerge. This could be done by parsing selected sources (e.g. *airlineroute.net* or *routesonline.com*) for codeshare updates and feeding the data to time-dependent adjacency matrices ($\boldsymbol{A_1}$, $\boldsymbol{A_2}$, $\boldsymbol{A_3}$ and so forth). In combination with empirical data on growth, dropout, and additional merging processes, this would allow to estimate realistic growth rates, degrees of interactions, and preferentiality. Thereafter, one could test the robustness of the findings given this important extension.

Fourthly, shocks represent interesting disturbances to a system. Extending my approach could introduce a continuous reassessment by agents over multiple periods to see whether the system tips or settles into a new equilibrium without further shocks. Another interesting direction is the observation by Arthur (1988) and Weitzel et al. (2006) that standard diffusion processes, once they gain momentum, often become self-fulfilling. Recasting my approach could be achieved by introducing a rationale to anticipate future developments in the agents' threshold values.

In addition to further elaborating the methods, tools, and models I have presented as the backdrop of my approach, another interesting research direction would be a to conduct a systematic, multi-disciplinary analysis incorporating the perspectives of multiple stakeholders on the consequences of big data methods using the airline industry as an example; such study could especially concern the widely-held underlying core assumption of the airline industry on the value of first degree price discrimination – charging the maximum price consumers are willing to pay. Isler and D'Souza (2009:255), two respected revenue management experts, note that "[p]rice discrimination can lead to increased efficiency and is tolerated by the public to a certain degree if it is not perceived as too unfair [...] the airline industry would not be able to offer its current public service level for both leisure and business customers without it". Price discrimination in the airline industry has gone hand-in-hand with increasingly complex algorithms as well as the technical development of advanced computerized distribution and revenue management systems (Isler and D'Souza 2009:255). I believe that the airline industry is an exceptional case in the respect that it has brought to perfection the use of big data methods. The case could thus be used to illuminate not whether price discrimination per-se is good or bad for the public but to answer questions such as: How does it affect various stakeholders? Who are the winners and the losers? What are the policy implications that follow from the use of big methods in that context? To what extent is the joint development of underlying assumptions, methods and tools reversible if societal norms change? The substantial qualitative data (cf. field data oS1-oS21) I have collected on pricing methods – mostly from the perspective of individual airlines – could be complemented and extended to cover such – more holistic – views on these, from a societal perspective, highly relevant questions (cf. Majchrzak and Markus 2013).

8.4.4 Implications for Research on Standard Diffusion

Turning in conclusion to broader theoretical implications, my results show that not only size matters for the success of the new standard but also the extent to which IATA is able to utilize the network structure in airline distribution with its close-knit interactions among carriers. Along with Afuah (2013), Weitzel et al.'s (2006), and Draisbach et al.'s (2013), I emphasized the implications of network topologies in explaining population-level diffusion outcomes. More broadly, my work is part of a maturing and fruitful stream of research that explains, from a network perspective, how individual level-interactions affect the diffusion of standards and innovations (Aral et al. 2009; Borgatti et al. 2009; Borgatti 2006; Jackson 2008b; Valente 2012). I believe that future research on standard diffusion will profit from going beyond agent-population level interactions by spending more time connecting individual agent interaction patterns with segment- and population level-outcomes.

My contribution over Weitzel et al. (2006) is as follows. Firstly, I explained individual level-adoption as a discrete, positional process in contrast to assuming simultaneous decision-making (or expectation building) by all agents in the network at the same time. New standards take time to spread and it is contingent on the position where a triggering event takes place if and when domino effects hit a particular agent. Hence, I can fit empirically observable time-dependent adoption dynamics such as the S-shaped curving of the fraction of adopters as a function of time as well as the non-spread of innovations. Secondly, I examined the implications of several previously unexplored theoretical (i.e. preferential attachment, decentralized and centralized structures) as well as one empirical network topology on standard diffusion outcomes. Interesting simulation results such as an exponential increase of the timing at which a tipping point occurs could be linked directly to a preferential attachment structure of a network. Thirdly, I demonstrated that interventions should not only consider individual agent's characteristics – i.e. an agent's size and positional importance – but also that these characteristics may vary across different groups of agents. Being small (in size and degree) in an alliance differed significantly from being small in another group. Fourthly, I incorporated different non-random intervention strategies, i.e. a group detection algorithm for maximum cliques, and showed that standardization success may be contingent on the chosen intervention strategy.

8.4.5 Implications for Research on Path Breaking

Regarding intervention strategies for deliberately breaking (inter-)organizational paths (Sydow et al. 2009), my results point to a possible two-step procedure to create new paths. In a first step, I suggest identifying a maximum clique of connected players. As a second step, one takes measures that this cohesive group of players adopts collectively. I showed that this form of collective action could outperform random interventions in a preferential attachment-type network. Furthermore, the maximum clique strategy performed akin to the switch of much larger subnetworks. My approach had the benefit of requiring no additional knowledge on the network other than its structure. However, my research also showed that these interventions must be fine-tuned: if one "attacks" random central (high-degree) players in an early stage, cascades often run dry as central (high-degree) players in a core-periphery network tend to connect to other central (high-degree) players, resulting in prevailing network effects that are hard to overcome. A team of several smaller and less central players will often be more ready to switch a new standard. Consider the example of Lufthansa as depicted in Figure 45. Several important players in the airline industry will influence Lufthansa's choice and create inertial forces to stick to established standard. Switching Lufthansa alone will thus be of little value. Airlines without these strong extents of interdependencies will have more room to maneuver. They are the first that *could* switch. Not until a sufficient base has been built in the periphery, will the core jump on the bandwagon (cf. Figure 54). I further emphasized the effect of agent heterogeneity on the success of creating a new path. Findings for size-adjusted thresholds suggested that average adoption thresholds can be lowered if some (small) agents thresholds are reduced even when others (large) players thresholds increase. This was due to the fact that initial momentum can be used to tip a core of large, densely-connected players. This is consistent with prior work on standardization processes that argues that standards often have to grow in a separate niche (Hanseth 2000:68), but adds to our understanding on when and how the thriving standard spills over from its self-contained compartment to a larger group of adopters.

8.4.6 Practical Implications

Practical implications for intervention strategies to "get the bandwagon rolling" are two-fold: first, my results suggest that IATA may foster the diffusion of the new standard most efficiently by mobilizing a maximum clique in the dense core that unleashes the necessary network effects and lets the standard gain momentum. I found that the codeshare network exhibits a core-periphery structure that was organized around several hubs demarked by the alliances (cf. Figure 43), restricting core members most severely. Targeted network interventions are hence needed that tip sets of key players collectively (cf. Valente 2012:50). Considering the results I have obtained from different intervention strategies (cf. Figure 64), my analysis suggests that a focus of resources onto a maximum clique in the core could significantly ease the overall transformation towards the new standard.

Second, my analysis suggests that IATA relieves peripheral airlines – necessary for the standard to gain additional momentum – most efficiently by lowering individual level adoption thresholds. Peripheral airlines are the first that *could* switch as they are least restricted by network effects giving them a privileged position. A limited size, different business model, or technology strategy and hence resource constraints of these more or less isolated carriers may, however, prevent them doing so (cf. Valente 1995; Valente 2012). I found an exponential decrease in the number of necessary interventions with decreases in individual level thresholds due to the "power law" structure of the network (cf. Figure 53a). By facilitating technological process and especially conversion technologies, such as efficient fare quote engines, IATA can thus spur peripheral carriers' adoption more efficiently.

Part IV

Conclusion

Chapter 9

Limitations, Implications, and Directions

9.1 Summary of Findings

My first research question aimed to explore how a system's growth logic affects path building. I have suggested a model of growing networks that has distinguished two different network influences linking individual agents' interactions with network-wide outcomes: network-size dependent effects (traditionally, network effects) – increasing network influences as a function of the network size – and spillover effects – influences to take action (e.g. to adopt a standard) as a function of the extent to which an agent's direct interaction partners have done so. Modeling and agent-based simulations produced valuable insights:

- I have brought to the forefront a not yet sufficiently theorized process – spillover effects across agents – that can lead to path-dependent outcomes
- Simulation results show that network effects and spillover effects are usefully distinguished as having different, non-monotonic effects on diffusion outcomes
- Consistent with seminal work on path dependence (Arthur 1989; David 1985), my results suggest that network effects will increase a system's susceptibility to lock-ins as network influences grow with the network size
- In contrast, spillover effects can make standards increasingly diffuse in segregated parts of a system. New elements are added to the system in nontrivial ways stabilizing the current configuration (e.g. heterogeneity of technologies in a system), not unlike the Polya Process

My second research question explored (*a*) the impact of interaction patterns for standard diffusion and (*b*) possibilities for targeted network interventions. Consistent with a tradition of innovation diffusion that distinguishes spontaneous and imitation-driven diffusion processes, I have build a model that conceptualizes the adoption of a new standard as a contagious process that potentially spills over via 'domino effects' rippling through the network. Some interesting insights emerged:

- The diffusion of a new standard is a time-dependent process; it is contingent on the position where triggering events occur whether and to what extent 'domino effects' arise
- In a network with a "power law" structure, the diffusion of a new standard may be very sensitive to changes in adoption thresholds
- Agent heterogeneity can matter to a different extent across groups, e.g. being small in an alliance may be very different from being small in another group
- Targeted network interventions, i.e. group detection algorithms, can outperform random interventions

Beyond the immediate implications for research on IT infrastructure path dependence, as a byproduct, I have developed a flexible simulator – consisting of a platform with several adaptable models – that can be used by other researchers.

9.2 Limits to Generality

Along with Davis et al. (2007), Gilbert and Troitzsch (2010), Vergne and Durand (2010), and Squazzoni (2012), I contend the value of agent-based modeling for theory building in the social sciences in general and for research on complex IT infrastructures in (inter-) organizational settings in particular. Modeling is, however, always a task of abstraction – not unlike drawing a cartoon – that is in danger of missing or mischaracterizing important properties, links, and dynamics of a particular system (cf. Holland 1995). Consistent with a long empirical tradition of scientific discovery that goes as far back as Popper's (1959) notion of falsifiability, I believe that theories must stand the test of reality to prove their usefulness. As suggested by Law (2007) and Gilbert and Troitzsch (2010), I have constructed my models closely to be intertwined between existing theories – top down – and empirical problems – bottom up – by interviewing domain experts and collecting data from the field. I have aimed to validate the models by linking them theoretically with existing models and, where necessary, arguing for the appropriateness of my assumptions. However, much more could be done to validate my results externally; a salient limitation shared with many simulation studies.

9.3 Theoretical and Practical Implications

9.3.1 Research on Path Dependence and Path Breaking

My results contribute to a recent stream of research that has started to categorize processes and mechanisms that potentially lead to path-dependent outcomes (Sydow et al. 2009). Based on the examples of global airline distribution IT and organizational IT infrastructures, I have conceptualized a spillover process in which each new element can reinforce the current configuration, which makes a system increasingly inert. Depending on the degree of interaction, this process potentially increases the probability that a system will lock in to one standard – if the degree of interaction is sufficiently high to allow action patterns to spill over from one part of the network to another – or segregated islands of shared technologies will arise.

In connection to that point, I emphasize that path dependence researchers can easily fall into the trap of assuming that every complementarity, mutual interdependency or spillover effect will result in a path-dependent trajectory in which the system locks in to a single standard, technology, or action pattern. This misperception can arise as network effects and spillover effects cannot be distinguished in situations where a set of fully coupled actors influence each other. In fact, this assumption – founded upon urn-type probability models – is a theoretical core of seminal work on path dependence by Arthur (1989) and remained unchallenged for a long time. Ironically, many important works on path dependence in other domains, such as organizational path dependence (Schreyögg and Sydow 2011; Sydow et al. 2009), or path-dependent IT infrastructures (Ciborra et al. 2000; Hanseth 2002) have built their theorizing on this restrictive assumption. The failure to account for real-world diffusion patterns such as islands of shared technology, local equilibria in close-knit circles of interaction partners, and the growth of heterogeneous hub-and-spoke structures lets me believe that my approach is a necessary recasting that hope-fully guides path dependence researcher to pay more attention to the way in which different elements of a system are coupled.

I further explored possibilities for path breaking. I have linked path dependence theory with a recent and fruitful stream of research on targeted network interventions (Valente 2012). Consistent with a tradition of path dependence research that construes path breaking as contingent on the effectiveness of external shocks (Vergne and Durand 2010), I have suggested a two-step procedure for path breaking based upon non-random network intervention strategies. I believe that my approach is a good starting point for further research on path breaking as it suggests to move on to the question of which interventions will be most effective in overcoming prevailing network effects. My results point to the interesting theoretical possibility that particular intervention strategies can be more effective than others in switching a system from one state (e.g. standard or action pattern) to another. Building upon my approach, future researchers can construct and test algorithms that aim to maximize the effectiveness of path breaking interventions.

9.3.2 Research on Network Models

I now discuss implications of my work along the lines of network formation and standard diffusion in networks. Firstly, I have presented a new model of growing networks. Few network formation models have combined non-random, growing networks with strategic agents selecting technologies based on a cost-benefit analysis (Jackson 2008b). My starting point was a hybrid random growth model (Jackson and Rogers 2007) where new agents form links to other nodes by attaching to a certain fraction of agents uniformly at random and to another fraction as "friends-of-friends", chasing adjacent links from their random encounters. My contribution over Jackson and Rogers (2007) is as follows. In addition to non-proportional, absolute growth, I have added proportional growth as a function of the network size, which enabled me to discern the consequences of spillover effects and network effects analytically. This is important as it combines two related, but previously unconnected branches of the literature on networks. Secondly, I have instantiated the model for Recycle Inc., a case company. In this context, I have added two useful extensions to network formation models: variances in the degrees of interaction and dropout processes. This approximates clustering coefficients and giant component sizes better than previous models.

Furthermore, I have presented a model that describes how standards diffuse in a network driven by shocks to particular nodes triggering subsequent cascades running through the network. Building on recent research on network interventions (Valente 2012), my contribution over Elliott et al. (2014) is as follows. I have conceptualized targeted network interventions by purposefully selecting groups of key players who were expected to maximize diffusion outcomes. I have applied a group detection algorithm that identifies maximum cliques and I have demonstrated by the means of simulation that my algorithm could outperform random interventions. Furthermore, I have enriched notions of agent heterogeneity by showing that behavior (adoption of standards) may not only be contingent on the individual agent's characteristics (e.g. size) but also its group membership (i.e. alliance membership). I believe this result is important as it demonstrates a need for research on how structural equivalence – the exposure of a group to a common “shock” – interacts with global diffusion outcomes (cf. Borgatti and Everett 1992; Burt 1987).

9.3.3 Research on Standard Diffusion and Information Infrastructures

I embraced a perspective of information infrastructure that centrally figures path dependencies in IT infrastructures, defined as a shared, evolving, open, standardized, and heterogeneous installed base (Hanseth 2002; Henningsson and Hanseth 2011). My work contributes to a maturing research stream on standard diffusion and adoption in information infrastructures (Hanseth 2000; Monteiro et al. 2013; Weitzel et al. 2006). My contribution to this literature is two-fold. First, prior work suggests that the installed base is most important to understand lock-ins in IT infrastructures as bandwagon effects, greater credibility of standards, and complementary products and services often reinforce one standard’s dominance and lock out alternative solutions. I conclude that the size of the installed base is only one factor in a complex array of variables that explain IT infrastructure heterogeneity. My results demonstrate that not all IT infrastructures are equally susceptible to lock-ins and, dependent on the growth logic of a system, path dependence can emerge not only on a global scale but also in segments and clusters of a network; segmented regimes – with multiple islands of shared technologies – are particularly important if we acknowledge that processes to adopt a standard are not only driven by – network size-dependent – network effects but also by direct spillover effects between coupled elements of a system. This micro-foundation helps to illuminate the puzzling variance in many important cases of path dependence. SAP landscapes in companies often co-exist with many other legacy systems and companies spend significant effort to consolidate their fragmented IT infrastructures (Engels et al. 2008; Masak 2006b). A strong community of Linux users thrives locally, despite a predominant Microsoft Windows path (Dobusch 2008, 2010; Shapiro and Varian 2008). Path dependence is inherently local. Paths decompose to agglomeration dynamics around hubs, which remains puzzling without a model that takes into account different growth logics in explaining the heterogeneity of standardization outcomes.

Secondly, the literature on information infrastructures suggests that “cultivation” – setting the right boundary conditions – instead of control is a necessary recasting when accounting for limited managerial variety to govern the evolution of IT infrastructures (Hanseth 2002). My research on booking class inertia adds an extreme case to this literature that substantiates limited managerial control in complex IT infrastructures.

Related to the previous point, my results on system embeddedness and continuance inertia suggest that IT managers may be better of focusing resources on *critical* IT systems with respect to their embeddedness in the overall IT architecture. These system are often central to support a company’s business processes but in case of capability shortcomings or discontinued support, they will be hard to abandon as they are connected to a large number of other systems or span between different parts of an IT architecture. Changes to these systems ripple through the entire architecture. Drawing on measures from network analysis, I suggested visualizations and measures from network analysis (i.e., degree and betweeness centrality) to identify these important systems. A managerial dashboard solution could build up on my approach.

9.3.4 Research and Practice in Revenue Management and Airline Distribution IT

Increasingly complex IT systems are a precondition to performing advanced airline pricing processes. The booking class standard has enabled a long, successful tradition of airline revenue management that manifests in advanced airline pricing processes and systems. Consistent with Ciborra et al. (2000), Masak (2006b), and Pavlou and El Sawy (2010), my research suggests that constant enhancements, improvisation, and workarounds are vital in complex IT infrastructural arrangements to create such IT-enabled capabilities. However, my research has also substantiated – consistent with Bartke (2013) – that the pervasive use of booking classes in today's airline distribution and pricing systems creates inertia when moving to newer pricing methods. As switching costs build up over extended time periods, changes to the overall system are increasingly out of reach. Tiny standards can travel long paths. Revenue management approaches presuming that existing systems and practices can be changed on-the-fly – e.g. to account for an indefinite number of price points – fall short. This challenges the rational underpinning of many revenue management approaches and dynamic pricing methods (refer to Talluri and van Ryzin 2005; Levin et al. 2009).

I hope that my research can impact managerial thinking and help to avoid some of the pitfalls that can arise when technical standards become a core pattern for companies' capabilities. I suggest reflexivity, mindfulness, and, most importantly, models that expatiate assumptions and allow the consideration of nonlinear dynamics and interaction patterns in complex systems.

In addition, my research illustrated that airline pricing is increasingly interorganizational, performed by various actors that span firm boundaries. Drawing on the example of booking class-usage in codeshares, my research has pointed to the fact that pressure to conform, peer influences, and learning from the experiences of others are important mechanisms to understand the processes that determine whether or not standards will spill over from one organization to another. My research suggests that network effects *and* spillover effects created a situation in which the booking class standard could become one of the key path dependencies in the industry. Illustrated by the example of SWISS, my findings also suggest that the improvisational capabilities of particular firms to work around the limitations of an inflexible standard can be undermined by pressures to conform in a larger web of influences from other organizations, vendors, and distribution partners.

Furthermore, my results lead me to suspect that a new distribution standard such as the NDC will not replace the booking class standard in the short or middle term. Taking into account the shared, heterogeneous, large-scale character of IT infrastructural arrangements (Ciborra et al. 2000; Hanseth and Lyytinen 2004; Henningsson and Hanseth 2011), my research suggests that a new standard will come to extend and complement existing airline distribution infrastructures. My results show that booking classes are inscribed and buried deeply within existing airline distribution IT infrastructures. Thus, the questions of whether the current standardization initiative by airline industry association IATA will succeed departs from the question of whether the booking class path can be broken. Both problem areas are intertwined but only to the extent that any new distribution standard in the airline industry will build upon, extend, and work around limitations of existing standards and infrastructures.

9.4 Agenda for Future Research

In addition to the research avenues I have outlined at the end of every main chapter, I emphasize three overarching directions to proceed further.

First, it seems promising to replicate my approach in other settings, especially in those in which IT infrastructure complexity built up over extended periods and seems to be set in stone. The banking industry, the insurance industry, the railway industry, and the telecommunication industry are excellent examples that let me believe that my work is by far not limited to the specific application domain of airline IT distribution standards. Most closely, in the railway industry, technical standards have also been inscribed in sales systems and reinforced over prolonged periods. I see apparent similarities with respect to problems of transforming business-critical systems to the internet age. In the banking industry, data standards for bank account transactions such as Deutsche Bank's "branch-account number" are a similar legacy from the early days of automation that today restricts the firm's scope of action. In the insurance industry, product definition in inventory systems also follows a specific logic that causes serious problems in adapting business processes and strategies to disrupted environments. These examples illustrate the need for further research on the organizational impacts of technical path dependencies. I see my approach as a prelude to a larger set of models that centrally figure interdependencies among elements in complex systems to investigate evolutionary processes in IT landscapes – on the individual, segment, and systemic level.

Second, I applied a network perspective to multiple levels of analysis in IT infrastructure contexts. I construed a company's IT architecture as a network in order to investigate architectural embeddedness, continuance inertia and evolution processes. I further constructed a model that examines standard diffusion in a network of organizations linked through, necessarily IT-based, codeshares. I believe agent-based models have the potential to combine multiple levels into a unified, multi-level model of IT infrastructure path dependence.

Finally, the increasing availability of large-scale data on information infrastructures enables novel investigations of IT infrastructure evolution processes. Our understanding of stabilizing and de-stabilizing processes within these infrastructures is still limited and held back by linear theories (Henningsson and Hanseth 2011). It is therefore promising to draw on these new data sets to foster original insights with regards to IT infrastructure inertia and change.

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Supplementary Materials

Figures S1 to S8

Tables S1 to S22

Field data as listed in Table S2 to Table S4 is available upon request from the author

Online Supplements

movie oS1	A demonstration of the *hybrid random growth model* featuring various start networks and new growth logics
movie oS2	A movie of the *contagion model* featuring empirical grounding of the underlying network structures and theoretical grounding with respect to the Roger's model of innovation diffusion
movie oS3	A movie of different *intervention strategies* and how the subsequent cascades unfold in the codeshare network
code example oS1	Marchov chain model
code example oS2	Polya Process and Balancing Process model
code example oS3	Network growth model
code example oS4	Compact network growth model (Recycle Inc.)
code example oS5	Contagion model
data set oS1	Codeshare network, adjacency matrix $\boldsymbol{A}$
data set oS2	Information systems (IS) network, adjacency matrix $\boldsymbol{B}$

Figure S1

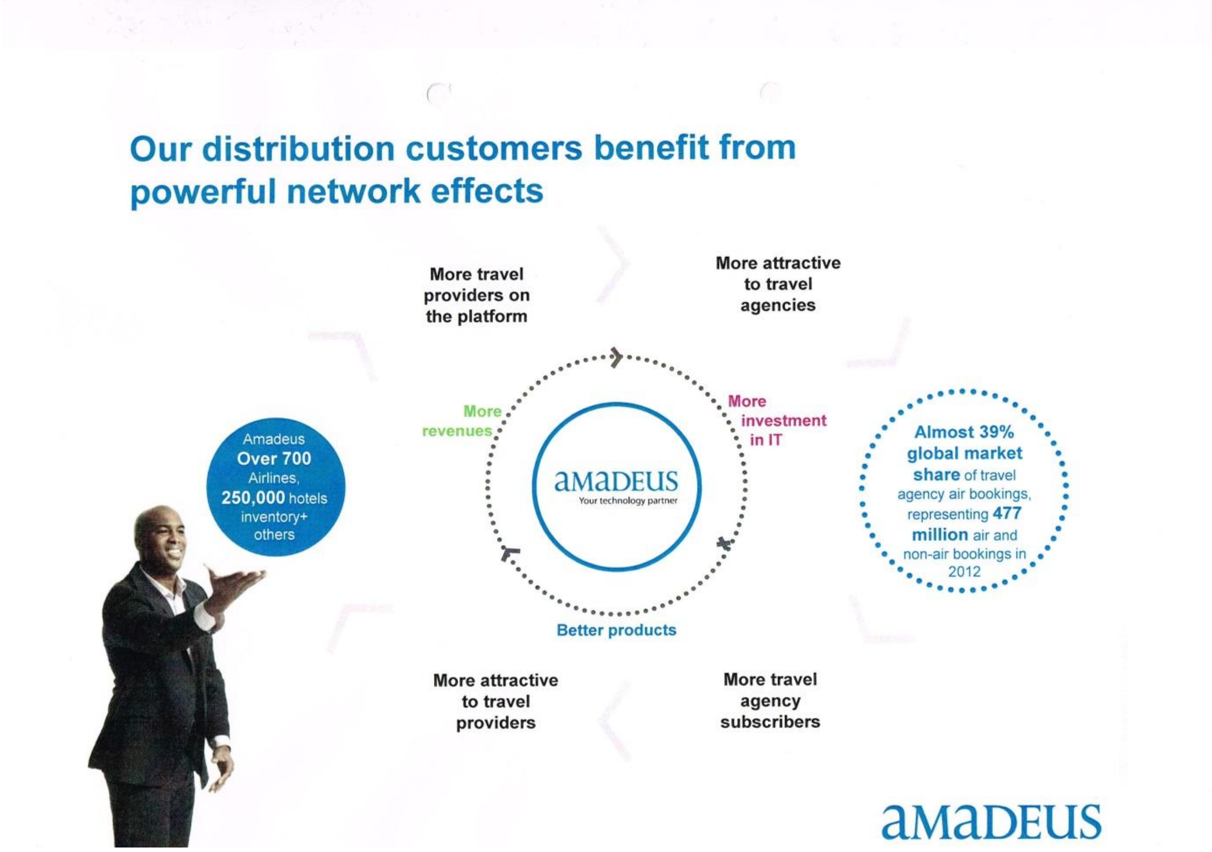
Availability display with booking classes. Source: Memo from email by airline distribution expert (refer to oS39)

```
THU 22AUG13 LONDON AREA /FRANKFURT 22/0000 22/2359 G*GAL
1 LHR FRA 0625 0905 LH 921 J9 C9 D9 Z7 P9 Y9 B9 M9 U9 H9#320C*E
2 LHR FRA 0700 0945 @AB5012 Y9 B9 H9 K9 M9 L9 V9 S9 N9 Q9#767C*E
3 LHR FRA 0700 0945 BA 902 J9 C9 D9 R9 I9 Y9 B9 H9 K9 M9#767C*E
4 LHR FRA 0715 0955 LH 923 J9 C9 D9 Z9 P9 Y9 B9 M9 U9 H9#321C*E
5 LCY FRA 0745 1015 @LH 927 J9 C9 D8 Z7 P6 Y9 B9 M9 U9 H9#E90C*E
6 LCY FRA 0745 1015 @NH6234 J4 C4 D4 Z4 P4 Y4 B4 M4 U4 H4#E90C*E
7 LCY FRA 0805 1035 @AB5088 Y9 B9 H9 K9 M9 L9 V9 S9 N9 Q9#E70C*E
8 LCY FRA 0805 1035 @BA8732 J9 C9 D9 R9 I9 Y9 B9 H9 K9 M9#E70C*E
```

The figure depicts a neutral display screen for a flight connection from London to Frankfurt from the Galileo GDS. The first line, on the top of the figure, shows the connection. After that, the further lines denote information in the following order: result number, departure airport, arrival airport, departure time, arrival time, flight number, booking class and availability of that class

Figure S2

Network effects for airline platforms for distribution. Source: Amadeus corporate presentation (refer to oS22)



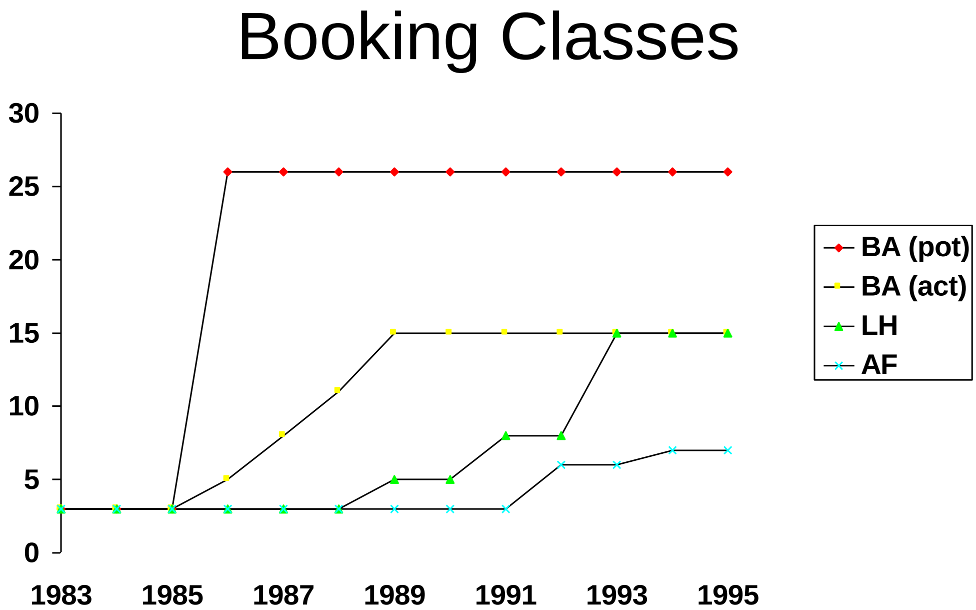
The figure depicts a slide from a corporate presentation of Amadeus in 2013.

Figure S3

Development of booking class usage of selected airlines from 1983 to 1995.

Source: Lehrer (1997:58)

The figure pinpoints the fact that each new generation of revenue management technology used booking classes more and more intensively. As shown in the figure, over the period from 1983 to 1995 the number of booking classes used at Lufthansa (LH) increased from three to fourteen. For British Airways (BA) it increased from three to fourteen. For Air France (AF), it increased from three to seven.



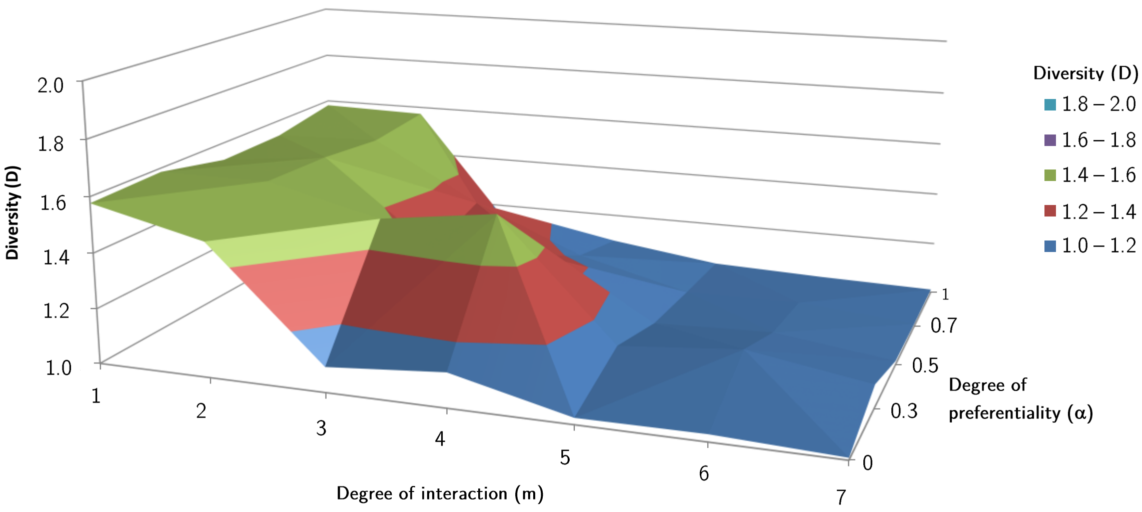
Sources: For BA: *British Airways News*, 13 Sept 1985 and interviews; for AF: Bordes-Pagès (1994b); for LH: *Fremdenverkehrswirtschaft Intern*, 4 July 1989; *Der Lufthanseat*, 19 June 1992 and 22 Jan 1993

Today, a carrier such as SWISS uses almost each booking class available as shown in the subsequent table (some booking classes are reserved for special purposes). The table shows the booking class hierarchy for SWISS intercontinental flights 2011 (refer to archival data oS37)

First Compartment	Business Compartment	Economy Compartment
F A O	J C D Z P	Y B M U H Q V W S T E L K

Figure S4

Effects of varying and degrees of interaction (m) and degrees of preferentiality (α) on diversity (D)

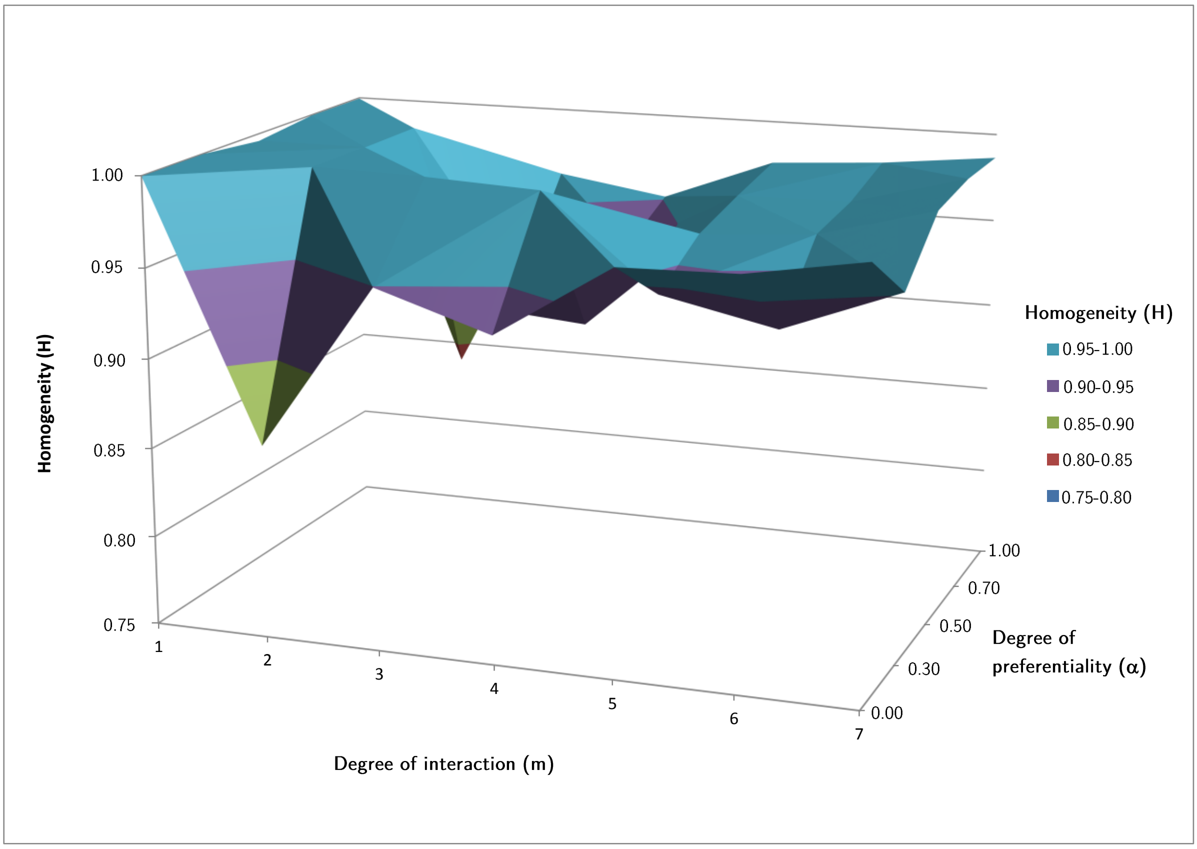


Diversity[1,2]		Degree of interaction (m)													
		Low				Medium								High	
		m = 1		m = 2		m = 3		m = 4		m = 5		m = 6		m = 7	
	Preferentiality	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
	preferential (α = 0)	1.58	0.37	1.48	0.35	1.09	0.20	1.12	0.24	1.02	0.08	1.03	0.11	1.01	0.02
hybrid	α = 0.3	1.59	0.34	1.59	0.33	1.49	0.37	1.54	0.34	1.12	0.23	1.16	0.26	1.09	0.22
hybrid	α = 0.5	1.53	0.35	1.58	0.34	1.26	0.34	1.27	0.33	1.06	0.13	1.07	0.21	1.01	0.03
hybrid	α = 0.7	1.54	0.34	1.55	0.32	1.32	0.34	1.15	0.28	1.04	0.14	1.05	0.14	1.01	0.02
	random (α = 1)	1.58	0.32	1.57	0.38	1.08	0.19	1.09	0.20	1.03	0.11	1.02	0.04	1.01	0.02

[1] Refer to Table S7, Exp. 13 for the experimental setup
[2] Average results for 100 simulation runs

Figure S5

Effects of varying and degrees of interaction (m) and degrees of preferentiality (α) on homogeneity (H)

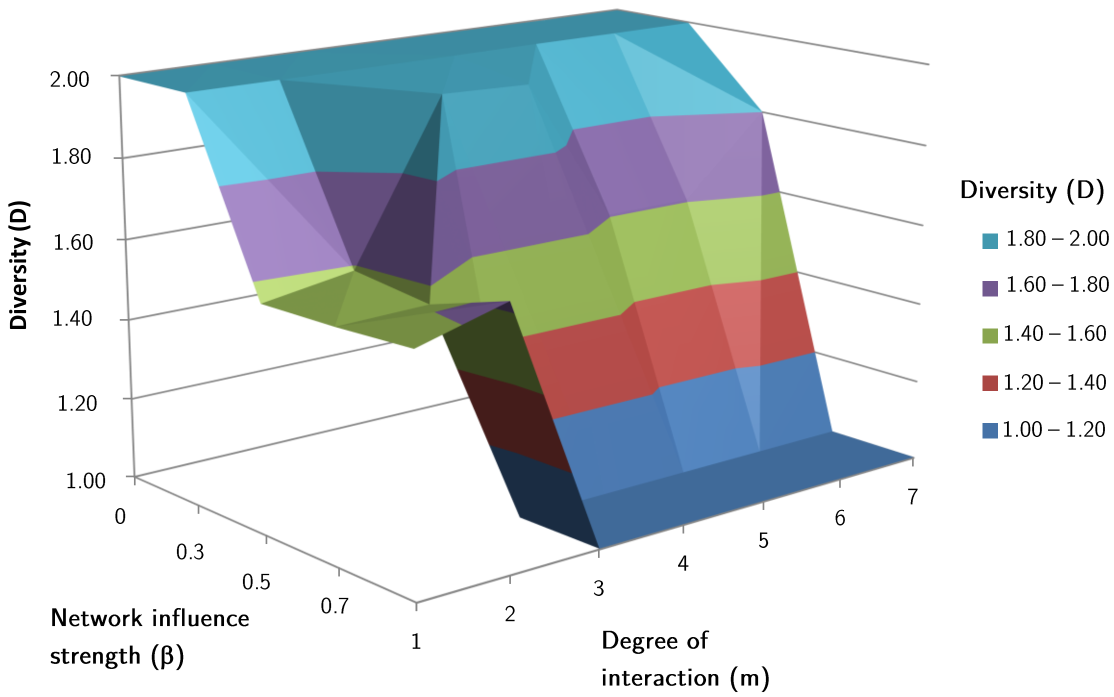


Homogeneity (H)[1,2]		Degree of interaction (m)													
		Low				Medium								High	
		m = 1		m = 2		m = 3		m = 4		m = 5		m = 6		m = 7	
	Preferentiality	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
	preferential $\alpha = 0$	1.00	0.00	0.86	0.09	0.95	0.06	0.93	0.09	0.97	0.04	0.97	0.05	0.98	0.02
hybrid	$\alpha = 0.3$	1.00	0.00	1.00	0.00	1.00	0.00	0.99	0.01	0.94	0.08	0.93	0.09	0.95	0.07
hybrid	$\alpha = 0.5$	1.00	0.01	1.00	0.00	0.91	0.09	0.90	0.09	0.96	0.07	0.96	0.07	0.98	0.03
hybrid	$\alpha = 0.7$	1.00	0.00	1.00	0.00	0.91	0.07	0.93	0.09	0.97	0.06	0.97	0.06	0.99	0.02
	random $\alpha = 1$	1.00	0.00	0.84	0.09	0.96	0.06	0.95	0.08	0.98	0.05	0.98	0.03	0.99	0.02

[1] Refer to Table S7, Exp. 13 for the experimental setup
[2] Average results for 100 simulation runs

Figure S6

Effects of varying network influence strengths (β) and degrees of interaction (m) on diversity (D)

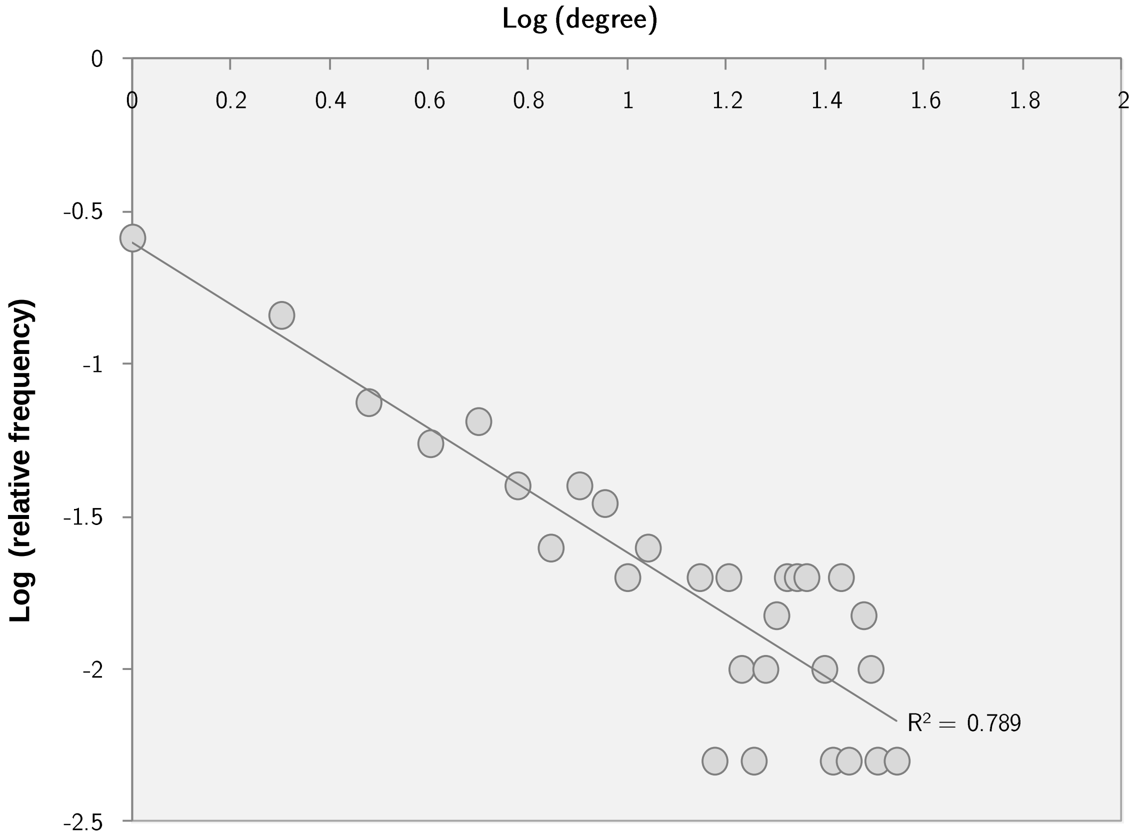


Diversity[1,2]	Degree of interaction (m)													
	Low				Medium								High	
	m = 1		m = 2		m = 3		m = 4		m = 5		m = 6		m = 7	
Network influence strength	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
β = 0	2.00	0.00	2.00	0.00	2.00	0.00	2.00	0.00	2.00	0.00	2.00	0.00	2.00	0.00
β = 0.3	2.00	0.00	2.00	0.00	2.00	0.00	2.00	0.00	2.00	0.00	2.00	0.00	2.00	0.00
β = 0.5	1.55	0.33	1.59	0.34	1.97	0.06	1.96	0.09	1.61	0.38	1.61	0.34	1.80	0.37
β = 0.7	1.56	0.31	1.57	0.35	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00
β = 1	1.57	0.33	1.63	0.32	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00	1.00	0.00

[1] Refer to Table S7, Exp. 11 for the experimental setup
[2] Average results for 100 simulation runs

Figure S7

Degree distribution of codeshare matrix $\boldsymbol{A}$ on log-log plot



I eliminated nodes from the data set that did not have any links (12 nodes out of 213 nodes). I then plotted relative frequency as a function of relative degree on a log-log plot as suggested by Jackson (2008a). The figure also shows that a linear regression model is able to explain 78.9 percent of the variance. This result reinforces my presumption that the network has a preferential attachment structure.

Figure S8

Extended model of airline interactions considering GDS, aggregators, and travel agents. Source: own investigation (based on sketch by RM expert in oS13)

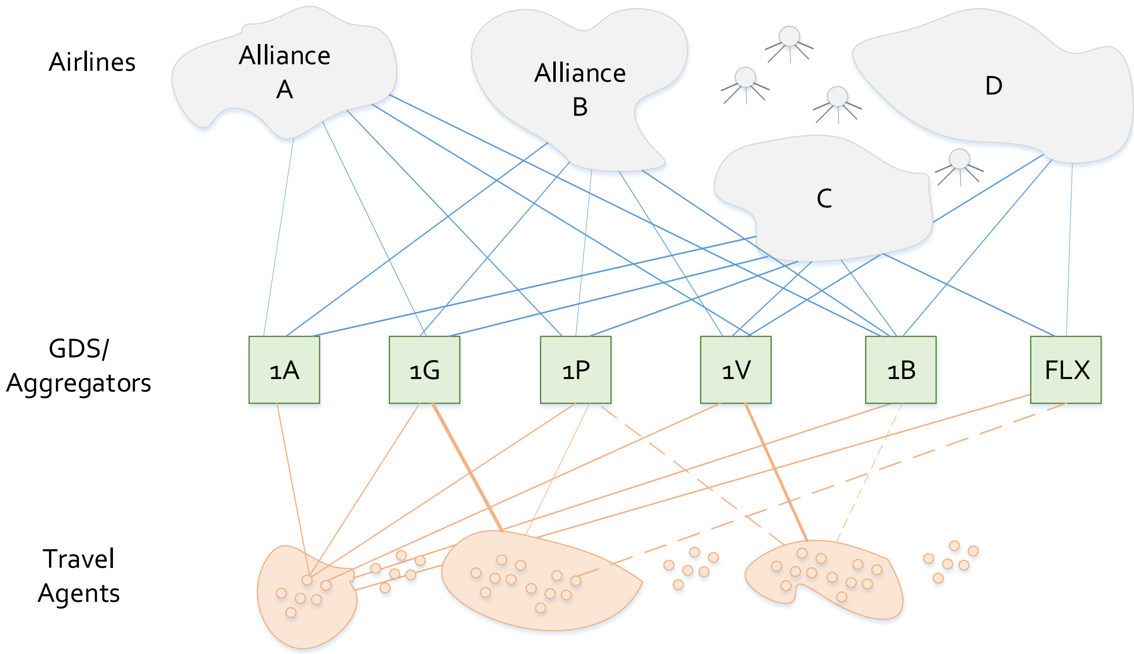


Table S1

Equation listing

2.1	Dynamic process
2.2	State-dependent process
2.3	Path-dependent process
2.4	Basic standardization problem
2.5	Ex-post standardization payoff
2.6	Standardization payoff with adaptive expectations
2.7	Multiple-standard payoff function
2.8	Bass model
4.1	Agent payoff function in growth model
4.2	Herfindahl index
4.3	Diversity index
4.4	Network-adjusted homogeneity for individual agent
4.5	Network-adjusted homogeneity
4.6	Individual misfits
5.1	Payoff function in Polya Process
6.1	Degree centrality
6.2	Betweeness centrality
6.3	Eigenvector centrality

Table S2

Airline distribution IT: expert interviews and observational data

Source	Dur.	Date	Firm[1]	Interviewee(s)	Content	Internal reference	Reference to field data
Interview	0.5h	Aug 12	AB	RM expert	Preliminary talk	Interview-00001 AB-IntAZ	oS1
Interview	1.0h	Aug 12	AB	RM expert	GDS, booking classes, RM	Interview-00002 AB-IntAZ	oS2
Interview	2.0h	Oct 12	AB	IT director	Airline distribution IT	Interview-00003 AB-IntAZ	oS3
Interview	2.0h	Jun 13	AB	Data analyst	Customer loyalty	Interview-00004 AB-IntAZ	oS4
Public talk	1.0h	Nov 12	AB	Pricing manager	Airline pricing, booking classes	Archiv-00004 AB-IntAZ	oS5
Oberservation	2d	Jan 12	AB	RM expert, 8 users	Revenue management systems	Obs-00011 AB-IntAZ	oS6
Interview	1.0h	Sep 12	LX	RM expert	GDS, dynamic pricing, booking classes	Interview-00031 LX-IntAZ	oS7
Workshop	1.5h	Mar 13	LX	2 RM experts	GDS, RM, booking classes	Interview-00032 LX-IntAZ	oS8
Workshop	1.0h	Mar 13	LX	2 RM experts	GDS, RM, booking classes	Interview-00033 LX-IntAZ	oS9
Workshop	1.5h	Mar 13	LX	2 RM experts	GDS, RM, booking classes	Interview-00034 LX-IntAZ	oS10
Phone interview	1.0h	May 13	LX	RM expert	New Distribution Capability	Interview-00035 LX-IntAZ	oS11
Workshop	2.0h	Aug 13	LX	2 RM experts	Fare filing, booking classes	Interview-00036 LX-IntAZ	oS12
Phone interview	1.5h	Dec 13	LX	2 RM experts	Standard diffusion in growing networks	Interview-00037 LX-IntAZ	oS13
Phone interview	1.5h	Apr 14	LX	RM expert	Model validation	Interview-00038 LX-IntAZ	oS14
Public talk	1.5h	Jul 12	O[2]	Manager e-commerce	Lufthansa e-commerce and processes	Archiv-00021 LH-IntAZ	oS15
Oberservation	0.5d	Jul 12	O[2]	4 airline RM experts	RM consortium	Archiv-00050 XX-IntAZ	oS16
Interview	1.0h	Dec 12	O[2]	RM expert	GDS, alliances, booking classes	Interview-00051 XX-IntAZ	oS17
Interview	2.0h	Jun 13	AM	Manager Quality	Amadeus History	Interview-00041 Am-IntAZ	oS18

Interview	2.0h	Jun 13	AM	Manager Quality	Amadeus History	Interivew-00042 Am-IntAZ	oS19
Interview	2.0h	Jul 13	AM	Manager Quality	Amadeus architecture, booking classes	Interivew-00043 Am-IntAZ	oS20
Email Interview	-	Jul 13	O[2]	Aviation expert	Embeddednesss of booking classes	Interview-00052 XX-IntAZ	oS21

[1] Short name or IATA code

[2] *O*ther indicates sources outside the companies directly tackled in the in-depth cases

Table S3

Airline distribution IT: archival data sources

Source	Date collect-ed	Firm[1]	Type	Pages	Content	Internal reference	Reference to field data
Archival	Feb 13	AM	Presentation	30	Corporate Presen-tation 2013	Archiv-00200 AM-IntAZ	oS22
Archival	Mar 13	AM	Report	200	Amadeus Annual Re-port 2012	Archiv-00204 AM-IntAZ	oS23
Archival	Jun 13	AM	Report	133	Strategy Intelligence Dashboard 2013	Archiv-00205 AM-IntAZ	oS24
Archival	Dec 12	AM	Brochure	8	Amadeus Data Center Infrastructure	Archiv-00206 AM-IntAZ	oS25
Archival	Jun 13	AB	Document	1	Buchungsklassen Bonusmeilengutschrift	Archiv-00234 AM-IntAZ	oS26
Archival	Jan 13	AB	Website	1	Buchungsklassen Bo-nus Meilen AB	Archiv-00235 AM-IntAZ	oS27
Archival	Dec 12	AB	Document	4	Konzernübergreifendes Informationssystem	Archiv-00240 AB-IntAZ	oS28
Archival	Dec 12	O[3]	Memo	1	Background talk	Archiv-00022 LH-IntAZ	oS29
Archival	Sep 12	O[3]	Website	1	Meilen sammeln beim Fliegen	Archiv-00252 LH-IntAZ	oS30
Archival	Dec 12	LX	Email memo	1	RM approach, booking classes	Archiv-00260 LX-IntAZ	oS31
Archival	May 13	LX	Email memo	1	Memo revenue man-agement box	Archiv-00261 LX-IntAZ	oS32
Archival	Aug 08	LX	Document	21	SWISS Preferred Fare Modell	Archiv-00265 LX-IntAZ	oS33
Archival	Aug 13	LX	Presentation	15	Dynamic Pricing and Future Distribution	Archiv-00267 LX-IntAZ	oS34
Archival	Jul 13	LX	Email memo	1	Preliminary talk SWISS	Archiv-00270 LX-IntAZ	oS35
Archival	Jul 13	LX	SWISS Magazine	1	SWISS vereinfacht Gruppenbuchungen	Archiv-00272 LX-IntAZ	oS36
Archival	Jun 13	LX	SWISS Webseite	1	SWISS Flugtarifkategorien	Archiv-00273 LX-IntAZ	oS37
Archival	Dec 13	LX	Document	1	SWISS Scheme Airline Industry Actors	Archiv-00274 LX-IntAZ	oS38
Archival	Apr 13	O[2]	Document	1	Neutral display screen from Galileo	Archiv-00303 XX-IntAZ	oS39
Archival	Nov 13	O[2]	Magazine	1	e-interface press an-nouncement	Archiv-00306 XX-IntAZ	oS40

[1] Short name or IATA code

[2] *O*ther indicates sources outside the companies directly tackled in the in-depth cases

Table S4

Recycle Inc.: interviews, observational and archival data sources

Source of data	Length	Date	Interviewee(s)	Content	Internal reference	Reference to field data
Interview	0.5h	Dec 2011	IT manager	Preliminary talk	Interview-00001 AL-IntAZ	oS41
Interview	1.5h	Jan 2012	2 IT employees	IT strategy Recycle Inc. waste operations	Interview-00002 AL-IntAZ	oS42
Interview	2.5h	Jan 2012	3 IT employees	Recyclix	Interview-00003 AL-IntAZ	oS43
Interview	1h	Mar 2012	IT manager	IT demand management waste operations	Interview-00004 AL-IntAZ	oS44
Interview	1.5h	Mar 2012	IT manager	IT strategy Recycle Inc. waste operations	Interview-00005 AL-IntAZ	oS45
Interview	1.5h	Mar 2012	Business manager	Business demands; Recyclix	Interview-00006 AL-IntAZ	oS46
Interview	1.5h	Mar 2012	2 business manager	Business demands; Recyclix	Interview-00007 AL-IntAZ	oS47
Interview	0.75h	Apr 2012	CIO	IT strategy and Recyclix	Interview-00008 AL-IntAZ	oS48
Interview	0.75h	Apr 2012	IT project manager	Project management southern region	Interview-00009 AL-IntAZ	oS49
Interview	1h	May 2012	Manager vendor	Recyclix; demand management; history	Interview-00010 AL-IntAZ	oS50
Interview	1h	May 2012	IT business analyst	IT landscape waste operations; Recyclix	Interview-00011 AL-IntAZ	oS51
Interview	1h	Jun 2012	Business manager	Recyclix	Interview-00012 AL-IntAZ	oS52
Interview	1h	Jun 2012	IT manager	Evaluation of findings	Interview-00013 AL-IntAZ	oS53
Direct observ.	4h	Jan 2012	IT employee; business user	Recyclix user training	Archiv-00050 AL-IntAZ	oS54
Archival	12 p.	1999	-	Article in practitioners journal (1999)	Archiv-00200AL-IntAZ	oS55

Table S5

Evidence for initial path dependence proposition with respect to booking class standard from various expert interviews

Quote	Reference
"It will be difficult to depart from the booking class logic as most RM systems are based on this science. I do not know I do hope some scientist must be thinking that perhaps the time came to accept a booking with a passenger value but perhaps I am now voyaging into Mars"	Aviation expert (refer to interview oS21)
"I would almost say, set in stone. Without a real chance to get really out. Except you make everything entirely different"	Airline expert and former board member (refer to memo oS29)
"With the booking class topic you have hit a complete lock-in target. For long, we try to get rid of these things, but in the meantime, not only a technical but also a cognitive lock-in is apparent for almost all stakeholders"	Revenue management expert (refer to archival data oS35)
"Of course, they are aligned to each other, because this is, I would say, a decade-long symbiosis of global distribution systems, reservation systems, and inventory systems. And thus, breaking up this symbiosis, I mean, what does it help to change my inventory [..] it still requires a nice, accurate partition building to 26 booking classes and the associated fares in the background"	Revenue management expert (refer to interview oS2)
"And these global distribution systems, which are first of all the window to the outside world, provide anyway just an availability display where I get only the letter of the booking class and a number. What help would it be if I had an inventory system in the background where I could configure 'this should now please cost 113.70', if this information is completely lost on the other channels."	Revenue management expert (refer to interview oS2)
"And this is just the data exchange among airlines; internal to GDS's also, in the end; and this was always based on IATA formats. There are entire lexica, bibles on particular messaging formats, which were originally based on Telex formats and that are valid until today"	GDS manager and distribution IT expert (refer to interview oS20)

Table S6

Usage of booking classes in airline processes in different domains

Activity	**Booking class usage**
Availability display	Airlines connecting to a GDS post availabilities for their predetermined *booking classes* in a standardized format (Talluri and van Ryzin 2005:523). Codes such as *Flight 314: Y4 M4 B0* indicate that four seats in class Y and M are available, and zero seats in class B. While classes Y and M are still 'open', B is 'closed'. An agent requesting itinerary information receives this information on the availability display and may perform a booking for a particular class (Talluri and van Ryzin 2005). See also the availability display example in Figure S1.
Billing & settlement	Settlement using the IATA Billing & Settlement Plan (BSP) is a monthly process between IATA-accredited agents and airlines using issued, booking class-based tickets (refer to oS33 for an example).
Check-in	Most steps from check-in to boarding directly or indirectly draw on the booking class standard. This includes the check-in process with customer identification, seating logic, validation of tickets, and regulatory steps, baggage management, standby management, boarding management by gate agents, and disruption management.
Codesharing availability exchange	Codesharing carriers have to resolve practical constraints on multiple levels including legal, technical, and organizational (Gerlach 2013:8). Focusing on the technical level, codesharing incorporates information sharing regarding the state of the other carrier's inventory. To achieve this, in many cases carriers map booking classes to exchange availability data between inventories. Consequently, carriers agree individual class mappings with each company they are codesharing with (cf. RM expert in interview oS12).
Corporate customer contracts	Many airlines have special arrangements with particular corporate customers guaranteeing them preferred fares. For several reasons (ensuring availability of these preferred fares in GDS/travel agent tools, routine development and so on) these contracts are often associated to booking classes (cf. RM expert in oS10).
Customer loyalty	Collecting status and bonus miles either relates to the *booking class* of a flight directly (e.g. for Miles & More in the Lufthansa Group where "the amount of bonus miles is determined by the booking class", cf. oS30) or indirectly via the fare level (e.g. Air Berlin where "the amount of bonus miles is determined by the service level, the booked fare and for long-haul flights additionally the actual distance"). In the latter case, fare levels are related to booking classes, e.g. Air Berlin's FlyFlex fare is associated to the booking classes *Y* and *B* (cf. oS27). Contingent on the internal structure of the airline's inventory, booking classes will be mapped to bonus mileage classes, which in turn determine the actual status and bonus miles (cf. oS26). Alternatively, one may simply use distance or number of flight segments to determine status and bonus miles (cf. data analyst in oS4).
"Dynamic" pricing	Some carriers began controlling their demand on a *booking-class level* by drawing on an advanced online process taking into account the fare(s) assigned to a booking class to determine to potential value of each booking. To achieve this, these airlines strive for restricting multi-fare usage and rather aim at simple fare structures (Isler

	and D'Souza 2009; see also oS31, oS33; RM experts in oS8, oS9, oS10).
Fare filing	Fares (indicated by a fare code which includes the booking class) – in particular, public fares – are uploaded to *ATPCo*, a third party, for publication in the GDS and subsequently subscribed by other internal and external stakeholders. This is a time-consuming, lagged, offline process (cf. Pölt 2011).
Fare quotation	Using a fare quote engine, the cheapest fare(s) for an origin-and-destination connection on a specific date in a specific booking class are quoted. Traditionally, the GDS' fare quote engine is quoted after the fare has been filed (ex-post), because of the complexity to build connections and to determine associated fare rules.
Group bookings	Similar to individual bookings, tickets are issued for group passengers. However, the group booking process deviates with respect to discounting, payment and so forth (cf. oS3). Carriers either maintain group booking capacity in special booking classes or assign group passengers to various booking classes 'on-the-fly' (RM expert in oS8)
Inventory control	The inventory implements the optimal availability function: It offers all products for which the optimal availability function is true, given the current vector of bookings, and prevents the sale of all other products (Bartke 2013:23). Actual inventory systems will constrain the set of availability functions that can be implemented. In practice, inventory systems may constrain the number of bookings in a certain booking class on a particular flight by booking limits or protection limits (Bartke 2013:23). Computerized revenue management systems control whether booking limits are exceeded and limit availabilities per *booking class* or *fare class* accordingly (Belobaba et al. 2009:88). Early revenue management systems simply partitioned available seats to set booking limits, while more recent systems use virtual nesting, providing 'buckets' for particular markets or a bid price control (Talluri and van Ryzin 2005:83-87). Alternatively, they can set a bid-price for each flight and only make those products available for which the price exceeds the sum of bid-prices of the flights in the itinerary (Bartke 2013:23). Combinations are also possible and in practical use. Airlines using bid price controls have to support seamless availability – using a particular EDIFACT standard – to exchange price and availability data between GDS and airline's inventory (Talluri and van Ryzin 2005: 86f. and 603f.).
Individual bookings	When a ticked is issued, the booking record (passenger name record) is used to assign a booking class to a ticket (Talluri and van Ryzin 2005).
Pricing	On an operational level, the activity of pricing is concerned with determining fares on a fare level whereas often multiple fare are assigned to one booking class (cf. Talluri and van Ryzin 2005; Belobaba et al. 2009; see also RM experts in oS7 and oS8).
Rebooking/ cancellations	Many airlines couple their refunds for no-shows or rebooking's to the booking class of the customer. In particular, these policies are tied to the fare or fare code (Talluri and van Ryzin 2005).
Revenue management demand forecasting	Bartke (2013) distinguishes three levels of revenue management demand forecasting: *Simple*, *market-sensitive*, and *price-sensitive* estimation models. Demand prognosis ("revenue forecasting") centers around the idea to estimate expected bookings for a particular origin and destination pair as a function of the number of expected bookings for available *booking classes* (simple estimation model). Market-sensitive and price-sensitive estimation models go one step further by making distribution as-

	sumptions incorporating more advanced machine learning techniques (Bartke 2013). The number of expected bookings is determined by historical booking data as well as further information. This process is called “unconstraining” (Cleophas 2009:25-27).
Revenue management optimization	Revenue management optimization combines the expected bookings for all availabilities received from the forecaster with a vector of prices of each product. It then finds the optimal availability that maximizes the function of prices given expected bookings (Bartke 2013:23). According to Bartke (2013:23), “this conceptually simple step can usually not be solved to optimality in practice due to the very large number of potential availability functions”. Consequently, heuristic methods are used in actual implementations to find an approximate solution to the optimization problem. The output of the optimizer is the optimal availability function which is sent to the inventory (Bartke 2013:23).
Revenue accounting & integrity	After the flight, issued tickets – including the passenger’s fare and booking class – are checked for accounting and revenue integrity purposes. In former times, this process was performed using paper-based tickets but today draws mainly on online tickets (cf. RM expert in oS8).
Reporting & controlling	Based on booking and ticketing information from the inventory, settlement system, check-in system, availability planning and so forth, airlines such as Air Berlin build data warehouses for central (revenue-)controlling purposes (cf. document oS28). This may either complement or actually compensate for weaknesses in revenue management solutions (cf. oS28).

Table S7

Setup for experiments on growing networks

					Initialization			Network formation						Strategic agents			
Exp.	Ch.	Internal	Name	Time	Diffusion	n_0	λ	Growth	β	q	m	m_{rel}	α	k	ν	b $\forall$ ν	a_k $\forall$ k
Exp. 1	5.2.1	Exp_01	absent	500	from hubs	10	-	hybrid	0	0	var.	-	0.5	2	2	0	0
Exp. 2	5.2.2	Exp_02	Arthur	1,000	unbiased	2	-	hybrid	1	1	-	1.0	1.0	2	2	0.1	*R*: [0.8 0.2] *S*: [0.2 0.8]
Exp. 3	5.2.2	Exp_03	Arthur	1,000	unbiased	2	-	hybrid	0.5	1	-	1.0	1.0	2	2	0.1	as above
Exp. 4	5.2.2	Exp_04	Arthur	1,000	unbiased	2	-	hybrid	0.5	1	-	1.0	1.0	2	2	1.0	as above
Exp. 5	5.2.2	Exp_05	Arthur	1,000	unbiased	2	-	hybrid	0.5	1	-	1.0	1.0	2	2	10.0	as above
Exp. 6	5.2.2	Exp_06	Arthur	1,000	unbiased	2	-	hybrid	0.5	1	-	1.0	1.0	5	5	0.1	R_1: [0.8,0.2,..,0.2] R_2: [0.2,0.8,..,0.2] ... R_5: [0.2,0.2,..,0.8]
Exp. 7	5.2.3	Exp_07	Polya	-	unbiased	2	-	hybrid	1	1	-	1.0	1.0	2	1	1.0	0
Exp. 8	5.3.1	Exp_12	growth	500	random	35	0.3	hybrid	1	0	var.	-	var.	2	2	100	0
Exp. 9	5.3.1	Exp_13	growth	500	random	35	0.3	hybrid	1	1	-	var.[1]	1.0	2	2	100	0
Exp. 10	5.3.1	Exp_14	growth	500	random	35	0.3	hybrid	1	1	-	var.[2]	1.0	2	2	100	0
Exp. 11	5.3.3	Exp_69	network effects	1,000	from hubs	10	-	hybrid	var.	0	var.	-	var.	2	2	100	*R*: [0.8 0.2] *S*: [0.2 0.8]
Exp. 12	5.3.3	Exp_69	network effects	1,000	unbiased	2	-	hybrid	var.	0	var.	-	var.	2	2	100	*R*: [0.8 0.2] *S*: [0.2 0.8]
Exp. 13	5.3.2	Exp_76	growth	1,000	from hubs	10	-	hybrid	1	0	var.	-	var.	2	2	100	0

[1] m_{rel} ... [0 0.1 1] where the ordering in the brackets is start value / increment / end value

[2] m_{rel} ... [0.025 0.025 0.3] where the ordering in the brackets is start value / increment / end value

Table S8

Effects of proportional growth ($p = 1$) on diversity (D)

Descriptives

Diversity (D)[1,2]

m_{rel}	N	Mean	Std. Dev.	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
0.1	100	1.2172	0.15479	0.01548	1.1865	1.2479	1.04	1.90
0.2	100	1.1054	0.06967	0.00697	1.0915	1.1192	1.04	1.59
0.3	100	1.0773	0.02608	0.00261	1.0721	1.0825	1.03	1.19
0.4	100	1.0775	0.03092	0.00309	1.0714	1.0837	1.03	1.20
0.5	100	1.0694	0.02501	0.00250	1.0644	1.0744	1.03	1.18
Total	500	1.1094	0.09606	0.00430	1.1009	1.1178	1.03	1.90

[1] The experimental setup is given in Table S7, Exp. 9

[2] Average results for 100 simulation runs

Table S9

Extended results for effects of proportional growth on diversity

Diversity (D)[1,2]

m_{rel}	N	Mean	Std. Dev.	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
0.000	100	1.9328	0.08285	0.00829	1.9163	1.9492	1.63	2.00
0.025	100	1.6494	0.25457	0.02546	1.5989	1.6999	1.14	2.00
0.050	100	1.3487	0.20195	0.02020	1.3087	1.3888	1.04	1.91
0.075	100	1.2106	0.10901	0.01090	1.1890	1.2322	1.05	1.49
0.100	100	1.2071	0.14813	0.01481	1.1777	1.2365	1.05	1.81
0.125	100	1.1468	0.09507	0.00951	1.1279	1.1657	1.04	1.53
0.150	100	1.1308	0.07039	0.00704	1.1168	1.1448	1.04	1.45
0.175	100	1.1217	0.07943	0.00794	1.1059	1.1375	1.04	1.63
0.200	100	1.1030	0.05324	0.00532	1.0924	1.1135	1.04	1.29
0.225	100	1.0971	0.04674	0.00467	1.0879	1.1064	1.03	1.33
0.250	100	1.0960	0.04770	0.00477	1.0866	1.1055	1.04	1.34
0.275	100	1.0821	0.03310	0.00331	1.0755	1.0887	1.04	1.27
0.300	100	1.0757	0.02497	0.00250	1.0708	1.0807	1.03	1.16
Total	1300	1.2463	0.27482	0.00762	1.2313	1.2612	1.03	2.00

[1] The experimental setup is given in Table S7, Exp. 10

[2] Average results for 100 simulation runs

Table S10

Recycle Inc.: empirical degree distributions of information system network

Degree	Log(degree)	Frequency	Rel. frequency	Log(rel. frequency)
1	0.000	136	0.642	-0.193
2	0.301	40	0.189	-0.724
3	0.477	16	0.075	-1.122
4	0.602	7	0.033	-1.481
5	0.699	1	0.005	-2.326
6	0.778	3	0.014	-1.849
7	0.845	2	0.009	-2.025
13	1.114	1	0.005	-2.326
18	1.255	2	0.009	-2.025
19	1.279	1	0.005	-2.326
23	1.362	1	0.005	-2.326
24	1.380	2	0.009	-2.025
Sum		212		

Table S11

Recycle Inc.: regression coefficients for quadratic model

The results illustrate the results from a quadratic regression on the degree distribution of one exemplary run using ‘model 9’. In the next appendix see the complete set of models.

Variable Processing Summary

		Variables	
		Dependent	Independent
		Log (rel. freq.)	Log (degree)
Number of Positive Values		0	12
Number of Zeros		0	1
Number of Negative Values		13	0
Number of Missing Values	User-Missing	0	0
	System-Missing	1	1

Model Summary and Parameter Estimates

Dependent Variable: Log (rel. freq.)

Equation	Model summary					Parameter estimates		
	R Square	F	df1	df2	Sig.	Constant	b1	b2
Quadratic	0.959	117.509	2	10	0.000	-0.045	-3.248	1.111

The independent variable is Log (degree).

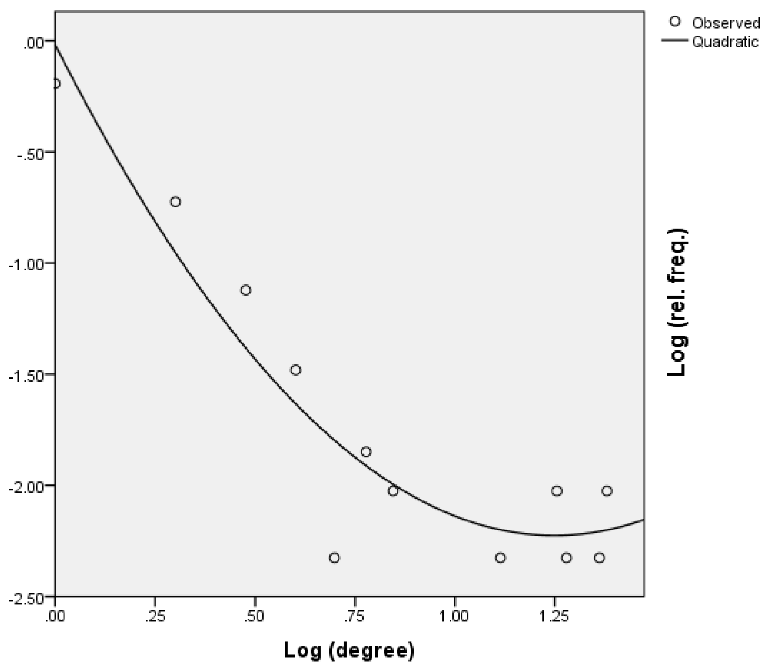


Table S12

A model of system embeddedness and continuance inertia

The goal: model the strength of a system's continuance inertia (y_i) as a function of its embeddedness in a network of information systems

Sketch of a theoretical model:

$$\mathbf{y_i = \phi \Sigma_{j \text{ in } N(g)} z_j + \Sigma_{m \text{ to } M} \beta_m x^m{}_i} + \eta + \varepsilon_i$$

where

x_m... is a vector of a system's individual characteristics explaining the internal variance of inertia (i.e., the number of users, size, and internal complexity)

β_m... is a vector of the strength of influence for each individual characteristic explaining the external variance of inertia

z_j... is a binary (dummy) variable taking the value of '1' if *j* is in *i*'s group of neighbors and '0' otherwise, and

ϕ... is the strength of the network multiplier (or "spillover effect") from the "reference group" of *j* neighbors

Table S13 Recycle Inc.: Fit of selected simulated models with network measures; model parameters in right column

Exp.	Model	Number of nodes	Number of links	Density	Density (norm.)	Average degree	Clust. coeff. (CC)	CC (norm.)	Average Path Length	Path Length (normalized)	Assortativity	Distance** (normalized)	start-network	no-initial-nodes	link-probability	degree of interaction	variance of interaction	alpha	dropout-rate	Time limit
	Empirical data	212,0	234,0	0,01000	1,000	2,179	0,241	1,000	4,357	1,000	-0,010									
21	Model-1*	168,2	248,4	0,01767	1,767	2,952	0,255	1,059	4,974	1,142	0,0763	0,612	random	5	0,50	1	2	0,70	0,0020	200
22	Model-2*	169,4	193,2	0,01350	1,350	2,278	0,293	1,214	6,589	1,512	0,0377	0,431	random	5	0,50	1	1	0,70	0,0020	200
23	Model-3*	168,6	139,9	0,00989	0,989	1,658	0,002	0,007	5,318	1,221	-0,0952	1,035	random	5	0,50	1	0	0,70	0,0020	200
24	Model-4*	168,5	305,6	0,02164	2,164	3,624	0,218	0,903	4,182	0,960	0,1026	1,366	random	5	0,50	1	3	0,70	0,0020	200
25	Model-5*	167,5	293,0	0,02100	2,100	3,496	0,318	1,321	4,486	1,030	0,0466	1,314	random	5	0,50	2	1	0,70	0,0020	200
26	Model-6*	168,1	276,1	0,01966	1,966	3,284	0,686	2,847	4,484	1,029	-0,0695	4,346	random	5	0,50	2	0	0,70	0,0020	200
27	Model-7*	168,3	245,2	0,01741	1,741	2,912	0,134	0,555	4,872	1,118	0,1081	0,761	random	5	0,50	1	2	0,80	0,0020	200
28	Model-8*	168,2	254,8	0,01811	1,811	3,027	0,370	1,536	5,057	1,161	0,0700	0,970	random	5	0,50	1	2	0,60	0,0020	200
19	Model-9*	205,0	205,1	0,00981	0,981	2,001	0,001	0,005	5,199	1,193	-0,1957	1,028	random	5	0,50	1	0	0,00	0,0000	200
19	Model-10*	205,0	405,1	0,01937	1,937	3,95239	0,081	0,337	3,370	0,774	-0,1551	1,369	random	5	0,50	2	0	0,00	0,0000	200
19	Model-11*	205,0	205,3	0,00982	0,982	2,003	0,002	0,007	5,149	1,182	-0,2009	1,019	random	5	0,50	1	0	0,10	0,0000	200
19	Model-12*	205,0	400,9	0,01917	1,917	3,911	0,084	0,350	3,359	0,771	-0,1604	1,316	random	5	0,50	2	0	0,10	0,0000	200
19	Model-13*	205,0	204,9	0,00980	0,980	1,999	0,002	0,008	5,209	1,196	-0,2095	1,023	random	5	0,50	1	0	0,20	0,0000	200
19	Model-14*	205,0	405,0	0,01937	1,937	3,951	0,077	0,321	3,375	0,775	-0,1550	1,390	random	5	0,50	2	0	0,20	0,0000	200
19	Model-15*	205,0	203,0	0,00971	0,971	1,980	0,001	0,006	5,217	1,197	-0,2031	1,029	random	5	0,50	1	0	0,30	0,0000	200
19	Model-16*	205,0	404,6	0,01935	1,935	3,947	0,692	2,870	4,639	1,065	-0,0545	4,374	random	5	0,50	2	0	0,30	0,0000	200
19	Model-17*	205,0	204,9	0,00980	0,980	1,999	0,002	0,007	5,295	1,215	-0,2045	1,034	random	5	0,50	1	0	0,40	0,0000	200
19	Model-18*	205,0	404,9	0,01936	1,936	3,950	0,692	2,870	4,598	1,055	-0,0553	4,378	random	5	0,50	2	0	0,40	0,0000	200
19	Model-19*	205,0	404,5	0,01934	1,934	3,946	0,692	2,870	4,549	1,044	-0,0515	4,372	random	5	0,50	1	0	0,50	0,0000	200
19	Model-20*	205,0	404,9	0,01936	1,936	3,950	0,693	2,874	4,625	1,062	-0,0545	4,394	random	5	0,50	2	0	0,50	0,0000	200
19	Model-21*	205,0	205,3	0,00982	0,982	2,002	0,003	0,013	7,483	1,717	-0,0274	1,489	random	5	0,50	1	0	0,60	0,0000	200
19	Model-22*	205,0	404,4	0,01934	1,934	3,946	0,692	2,871	4,620	1,060	-0,0498	4,375	random	5	0,50	2	0	0,60	0,0000	200
19	Model-23*	205,0	205,3	0,00982	0,982	2,003	0,003	0,012	7,572	1,738	-0,0335	1,520	random	5	0,50	1	0	0,70	0,0000	200
19	Model-24*	205,0	404,6	0,01935	1,935	3,947	0,693	2,877	4,603	1,057	-0,0574	4,400	random	5	0,50	2	0	0,70	0,0000	200
19	Model-25*	205,0	205,0	0,00981	0,981	2,000	0,003	0,012	7,473	1,715	-0,0305	1,488	random	5	0,50	1	0	0,80	0,0000	200
19	Model-26*	205,0	405,2	0,01938	1,938	3,953	0,024	0,099	3,880	0,890	0,0575	1,704	random	5	0,50	2	0	0,80	0,0000	200
19	Model-27*	205,0	205,1	0,00981	0,981	2,001	0,003	0,013	7,546	1,732	-0,0350	1,510	random	5	0,50	1	0	0,90	0,0000	200
19	Model-28*	205,0	405,0	0,01937	1,937	3,951	0,024	0,102	3,879	0,890	0,0642	1,697	random	5	0,50	2	0	0,90	0,0000	200
19	Model-29*	205,0	205,1	0,00981	0,981	2,001	0,003	0,012	7,541	1,731	-0,0256	1,510	random	5	0,50	1	0	1,00	0,0000	200
19	Model-30*	205,0	404,9	0,01936	1,936	3,950	0,024	0,100	3,882	0,891	0,0555	1,699	random	5	0,50	2	0	1,00	0,0000	200
20	Model-31*	255,0	350,9	0,01084	1,084	2,752	0,286	1,187	5,959	1,368	0,0713	0,177	random	5	0,50	1	1	0,70	0,0000	250
20	Model-32*	225,5	277,7	0,01097	1,097	2,462	0,290	1,204	6,586	1,512	0,0474	0,313	random	5	0,50	1	1	0,70	0,0010	250
20	Model-33*	201,0	223,1	0,01109	1,109	2,218	0,295	1,223	7,304	1,676	0,0366	0,519	random	5	0,50	1	1	0,70	0,0020	250
20	Model-34*	179,2	181,6	0,01137	1,137	2,025	0,290	1,202	7,232	1,660	0,0247	0,495	random	5	0,50	1	1	0,70	0,0030	250
20	Model-35*	160,2	148,9	0,01167	1,167	1,857	0,296	1,228	6,352	1,458	0,0265	0,289	random	5	0,50	1	1	0,70	0,0040	250
20	Model-36*	255,0	452,9	0,01399	1,399	3,552	0,252	1,046	4,688	1,076	0,1278	**0,167**	random	5	0,50	1	2	0,70	0,0000	250
20	Model-37*	226,1	359,4	0,01412	1,412	3,178	0,252	1,047	4,980	1,143	0,1048	0,193	random	5	0,50	1	2	0,70	0,0010	250
20	Model-38*	200,8	288,9	0,01440	1,440	2,875	0,250	1,039	5,289	1,214	0,0816	0,241	random	5	0,50	1	2	0,70	0,0020	250
20	Model-39*	177,6	236,1	0,01504	1,504	2,655	0,256	1,061	5,508	1,264	0,0832	0,327	random	5	0,50	1	2	0,70	0,0030	250
20	Model-40*	161,1	196,6	0,01522	1,522	2,437	0,269	1,115	5,833	1,339	0,0769	0,401	random	5	0,50	1	2	0,70	0,0040	250

* Results averaged for 100 runs per model; note that dot is used as a decimal delimiter in this table (European data format)
** Distance is calculated as the mean squared difference between model and empirical data in normalized density, clustering coefficient, and average path length

Exp.	Model	start-network	no-initial-nodes	link-probability	degree of interaction	variance of interaction	alpha	dropout-rate	Time limit	R² (sim.): model fit	Adjusted R²	Std.error of estimate	KORREL (linear): Fit with data	Logdegree	Logdegree ^2	Logdegree ^3	(Constant)
21	Model-1*	random	5	0,50	1	2	0,70	0,0020	200	0,959	0,951	0,135	**0,755**	-0,137	-1,219		-0,504
22	Model-2*	random	5	0,50	1	1	0,70	0,0020	200	0,957	0,940	0,144	**0,769**	-0,374	-1,247		-0,388
23	Model-3*	random	5	0,50	1	0	0,70	0,0020	200	0,913	0,855	0,280	**0,778**	-0,873	-1,971		-0,206
24	Model-4*	random	5	0,50	1	3	0,70	0,0020	200	0,851	0,822	0,225	**0,759**	-0,163	-1,019		-0,560
25	Model-5*	random	5	0,50	2	1	0,70	0,0020	200	0,966	0,958	0,113	**0,670**	1,117	-2,214		-0,751
26	Model-6*	random	5	0,50	2	0	0,70	0,0020	200	0,958	0,944	0,133	**0,679**	6,039	-12,758	6,004	-1,257
27	Model-7*	random	5	0,50	1	2	0,80	0,0020	200	0,962	0,952	0,140	**0,694**	0,967	-2,501		-0,612
28	Model-8*	random	5	0,50	1	2	0,60	0,0020	200	0,859	0,818	0,247	**0,719**	0,442	-1,932		-0,556
19	Model-9*	random	5	0,50	1	0	0,00	0,0000	200	0,959	0,951	0,152	**0,941**	-3,248	1,111		-0,045
19	Model-10*	random	5	0,50	2	0	0,00	0,0000	200	0,936	0,927	0,181	**0,938**	-4,753	1,556		1,184
19	Model-11*	random	5	0,50	1	0	0,10	0,0000	200	0,958	0,946	0,165	**0,925**	-2,610	0,706		-0,124
19	Model-12*	random	5	0,50	2	0	0,10	0,0000	200	0,961	0,956	0,130	**0,935**	-4,202	1,326		0,936
19	Model-13*	random	5	0,50	1	0	0,20	0,0000	200	0,964	0,955	0,148	**0,914**	-2,496	0,554		-0,144
19	Model-14*	random	5	0,50	2	0	0,20	0,0000	200	0,912	0,900	0,205	**0,934**	-4,372	1,358		1,036
19	Model-15*	random	5	0,50	1	0	0,30	0,0000	200	0,940	0,927	0,187	**0,942**	-3,192	1,123		-0,082
19	Model-16*	random	5	0,50	2	0	0,30	0,0000	200	0,897	0,878	0,232	**0,900**	-2,859	0,445		0,559
19	Model-17*	random	5	0,50	1	0	0,40	0,0000	200	0,892	0,865	0,254	**0,940**	-3,795	1,692		-0,009
19	Model-18*	random	5	0,50	2	0	0,40	0,0000	200	0,929	0,919	0,190	**0,934**	-4,474	1,390		1,108
19	Model-19*	random	5	0,50	1	0	0,50	0,0000	200	0,877	0,846	0,251	**0,460**	8,370	-14,479	6,051	-1,954
19	Model-20*	random	5	0,50	2	0	0,50	0,0000	200	0,966	0,958	0,138	**0,357**	8,822	-13,950	5,436	-2,227
19	Model-21*	random	5	0,50	1	0	0,60	0,0000	200	0,905	0,874	0,282	**0,819**	-1,446	-0,830		-0,198
19	Model-22*	random	5	0,50	2	0	0,60	0,0000	200	0,943	0,929	0,171	**0,348**	9,259	-14,934	5,974	-2,249
19	Model-23*	random	5	0,50	1	0	0,70	0,0000	200	0,987	0,982	0,092	**0,761**	-0,364	-1,952		-0,303
19	Model-24*	random	5	0,50	2	0	0,70	0,0000	200	0,899	0,884	0,225	**0,899**	-2,919	0,445		0,569
19	Model-25*	random	5	0,50	1	0	0,80	0,0000	200	0,973	0,959	0,122	**0,809**	-1,067	-0,831		-0,270
19	Model-26*	random	5	0,50	2	0	0,80	0,0000	200	0,957	0,947	0,120	**0,766**	-0,311	-1,216		-0,245
19	Model-27*	random	5	0,50	1	0	0,90	0,0000	200	0,985	0,980	0,094	**0,778**	-0,683	-1,526		-0,284
19	Model-28*	random	5	0,50	2	0	0,90	0,0000	200	0,919	0,901	0,197	**0,798**	-0,837	-0,921		-0,061
19	Model-29*	random	5	0,50	1	0	1,00	0,0000	200	0,949	0,928	0,183	**0,808**	-1,141	-0,923		-0,247
19	Model-30*	random	5	0,50	2	0	1,00	0,0000	200	0,956	0,948	0,155	**0,763**	-0,297	-1,388		-0,195
20	Model-31*	random	5	0,50	1	1	0,70	0,0000	250	0,899	0,878	0,246	**0,781**	-0,573	-1,144		-0,387
20	Model-32*	random	5	0,50	1	1	0,70	0,0010	250	0,944	0,925	0,195	**0,723**	0,494	-2,495		-0,448
20	Model-33*	random	5	0,50	1	1	0,70	0,0020	250	0,965	0,947	0,155	**0,711**	1,003	-3,565		-0,431
20	Model-34*	random	5	0,50	1	1	0,70	0,0030	250	0,979	0,971	0,113	**0,765**	-0,346	-1,469		-0,368
20	Model-35*	random	5	0,50	1	1	0,70	0,0040	250	0,908	0,862	0,304	**0,730**	0,482	-3,447		-0,346
20	Model-36*	random	5	0,50	1	2	0,70	0,0000	250	0,947	0,936	0,144	**0,705**	0,543	-1,686		-0,659
20	Model-37*	random	5	0,50	1	2	0,70	0,0010	250	0,947	0,932	0,129	**0,724**	0,301	-1,589		-0,572
20	Model-38*	random	5	0,50	1	2	0,70	0,0020	250	0,960	0,947	0,110	**0,730**	0,244	-1,681		-0,528
20	Model-39*	random	5	0,50	1	2	0,70	0,0030	250	0,962	0,949	0,138	**0,703**	0,909	-2,696		-0,546
20	Model-40*	random	5	0,50	1	2	0,70	0,0040	250	0,988	0,983	0,074	**0,716**	0,597	-2,362		-0,497

Table S14

Results for exponential regression of tipping point timing (*noshocks_target*) for varying thresholds (θ)

Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
0.978	0.956	0.955	0.356

The independent variable is θ.

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	1081.354	1	1081.354	8554.445	0.000
Residual	50.311	398	0.126		
Total	1131.665	399			

The independent variable is θ.

Coefficients

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
threshold_teta	14.706	0.159	0.978	92.490	0.000
(Constant)	0.908	0.027		33.617	0.000

The dependent variable is noshocks_target.

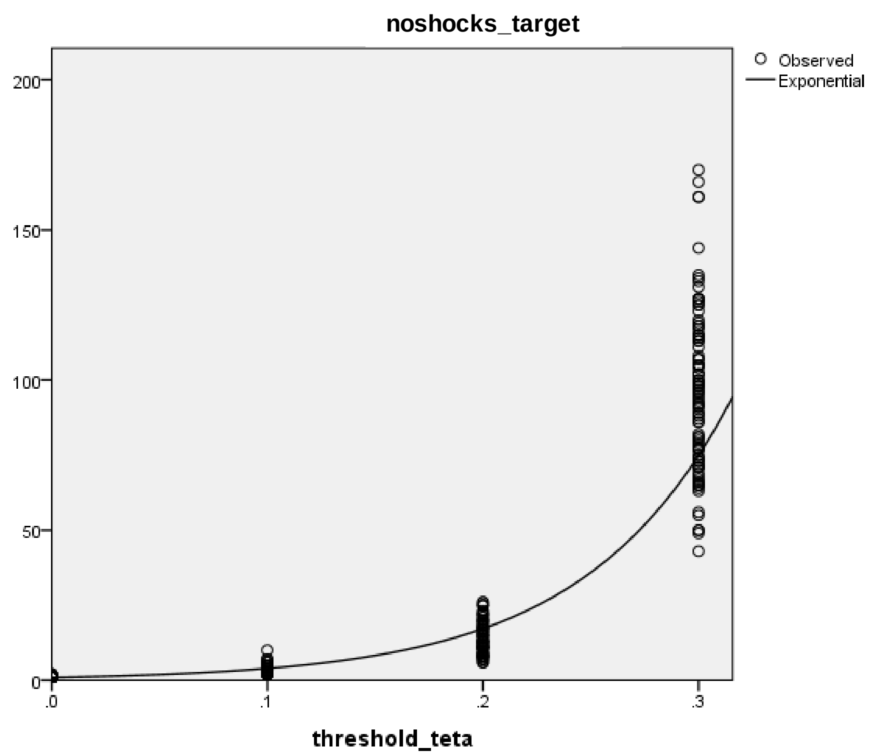


Table S15

Results of linear regression of tipping point intensity as a function of varying adoption thresholds (θ)

Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
0.942	0.888	0.888	0.081

The independent variable is θ.

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	20.770	1	20.770	3149.342	0.000
Residual	2.625	398	0.007		
Total	23.394	399			

The independent variable is θ.

Coefficients

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
threshold_teta	-2,.38	0.036	-0.942	-56.119	0.000
(Constant)	0.932	0.007		137.148	0.000

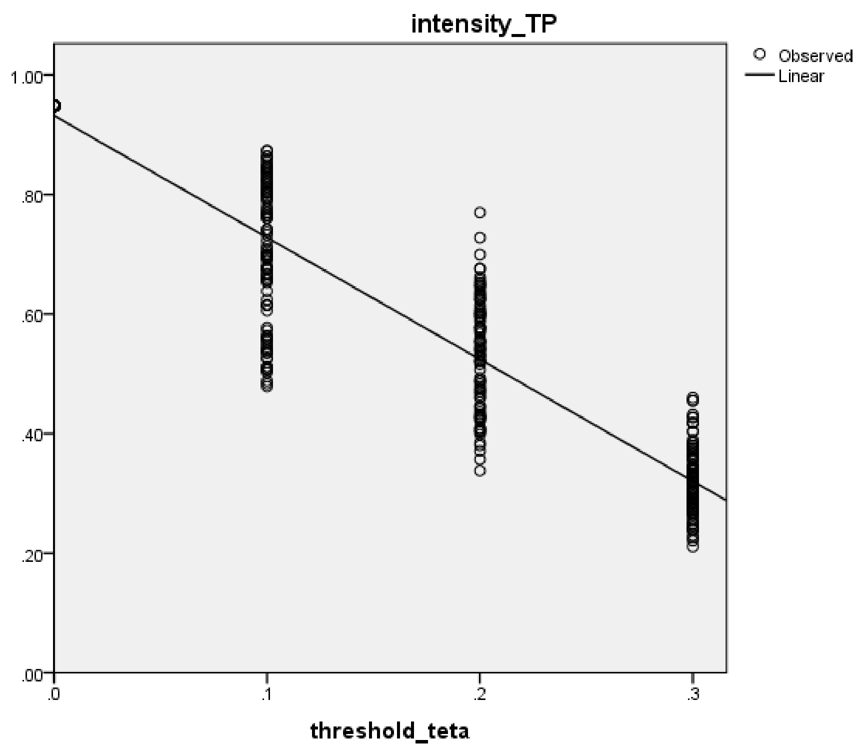


Table S16

Results of linear regression of squared average adoption period (*noshocks_squared*) as function of the agents' size

Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
0.718	0.516	0.511	333.094

The independent variable is size.

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	11231431.489	1	11231431.489	101.228	0.000
Residual	10540390.972	95	110951.484		
Total	21771822.461	96			

The independent variable is size.

Coefficients

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Size	4.638	0.461	0.718	10.061	0.000
(Constant)	462.784	49.287		9.390	0.000

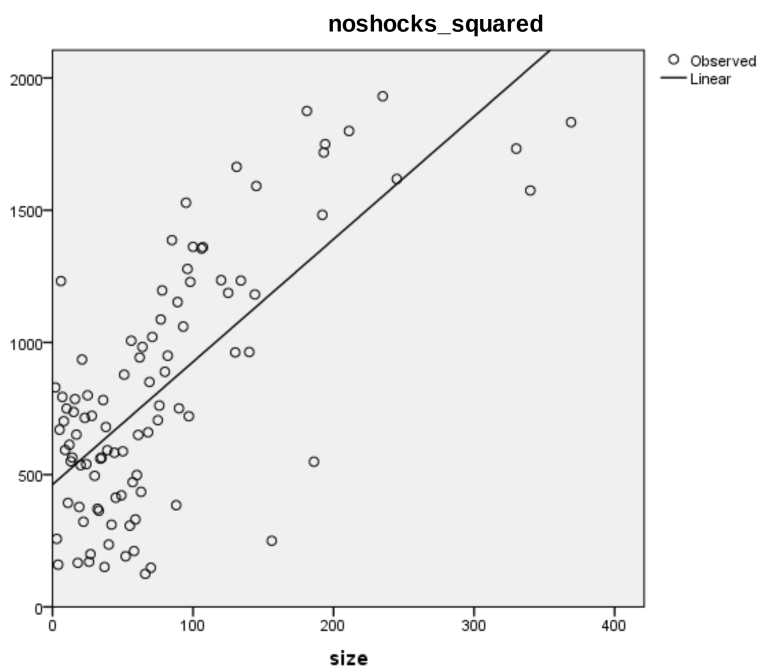


Table S17

Results of linear regression of average switch period (*noshocks*) as function of agents' degree (number of codeshare links)

Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
0.702	0.492	0.477	5.892

The independent variable is degree.

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	1110.778	1	1110.778	31.999	0.000
Residual	1145.523	33	34.713		
Total	2256.301	34			

The independent variable is degree.

Coefficients

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Degree	0.529	0.094	0.702	5.657	0.000
(Constant)	19.933	1.982		10.058	0.000

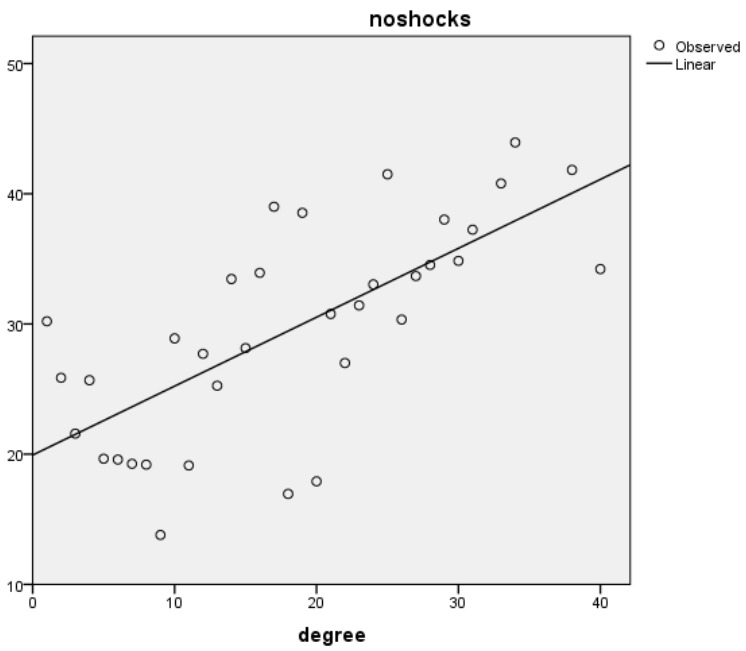


Table S18

Results of linear regression of average adoption period (*noshocks*) as function of degree across alliance-members (1) and non-alliance members (0)

Variables Entered/Removed[a]

Alliance	Model	Variables Entered	Variables Removed	Method
0	1	degree[b]	.	Enter
1	1	degree[b]	.	Enter

a. Dependent Variable: noshocks

b. All requested variables entered.

Model Summary

Alliance	Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
0	1	0.074[a]	0.005	-0.057	8.24663
1	1	0.570[a]	0.325	0.313	7.39218

a. Predictors: (Constant), degree

ANOVA[a]

Alliance	Model		Sum of Squares	df	Mean Square	F	Sig.
0	1	Regression	6.004	1	6.004	0.088	0.770[b]
		Residual	1088.110	16	68.007		
		Total	1094.115	17			
1	1	Regression	1422.033	1	1422.033	26.023	0.000[b]
		Residual	2950.797	54	54.644		
		Total	4372.830	55			

a. Dependent Variable: noshocks

b. Predictors: (Constant), degree

Coefficients[a]

Alliance	Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
			B	Std. Error	Beta		
0	1	(Constant)	21.628	3.545		6.100	0.000
		degree	0.085	0.287	0.074	0.297	0.770
1	1	(Constant)	21.423	1.929		11.108	0.000
		degree	0.502	0.098	0.570	5.101	0.000

a. Dependent Variable: noshocks

Table S19

Linear regression of squared average adoption period (*noshocks * noshocks*) as function of size across (*a*) alliance-members and (*b*) non-alliance members

Variables Entered/Removed[a]

Alliance	Model	Variables Entered	Variables Removed	Method
0	1	size[b]	.	Enter
1	1	size[b]	.	Enter

a. Dependent Variable: noshocks_squared

b. All requested variables entered.

Model Summary

Alliance	Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
0	1	0.059[a]	0.003	-0.014	357.98715
1	1	0.739[a]	0.546	0.540	365.76770

a. Predictors: (Constant), size

ANOVA[a]

Alliance	Model		Sum of Squares	df	Mean Square	F	Sig.
0	1	Regression	25526.390	1	25526.390	0.199	0.657[b]
		Residual	7432978.248	58	128154.797		
		Total	7458504.637	59			
1	1	Regression	11431919.580	1	11431919.580	85.449	0.000[b]
		Residual	9498806.652	71	133786.009		
		Total	20930726.233	72			

a. Dependent Variable: noshocks_squared

b. Predictors: (Constant), size

Coefficients[a]

alliance	Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
			B	Std. Error	Beta		
0	1	(Constant)	590.898	74.757		7.904	0.000
		size	0.622	1.394	0.059	0.446	0.657
1	1	(Constant)	446.173	69.470		6.423	0.000
		size	5.209	0.563	0.739	9.244	0.000

a. Dependent Variable: noshocks_squared

Table S20

Effect of different intervention strategies *(random-nof, max-clique, star)* on fraction of adopters for varying threshold levels (ϴ)

Threshold (ϴ)	Intervention strategy[1]					
	Random-nof		Max-clique		Star	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
0	0.78	0.06	0.90	0.02	0.91	0.02
0.1	0.67	0.07	0.86	0.03	0.87	0.03
0.2	0.52	0.11	0.77	0.03	0.81	0.02
0.3	0.35	0.12	0.68	0.04	0.75	0.02
0.4	0.20	0.08	0.61	0.04	0.71	0.01
0.5	0.16	0.06	0.49	0.07	0.69	0.01
0.6	0.12	0.05	0.33	0.04	0.63	0.02
0.7	0.10	0.04	0.26	0.02	0.59	0.01
0.8	0.08	0.02	0.23	0.02	0.53	0.01
0.9	0.07	0.02	0.19	0.02	0.51	0.01
1	0.06	0.02	0.15	0.01	0.39	0.01
Total	**0.28**	**0.26**	**0.50**	**0.27**	**0.67**	**0.15**

[1] Average results for 100 simulation runs

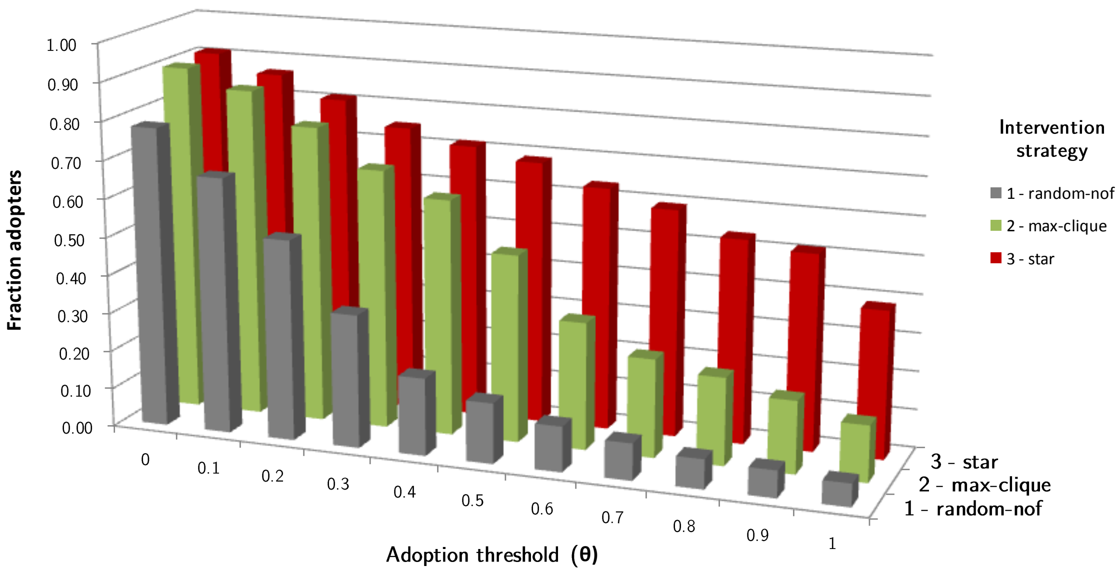
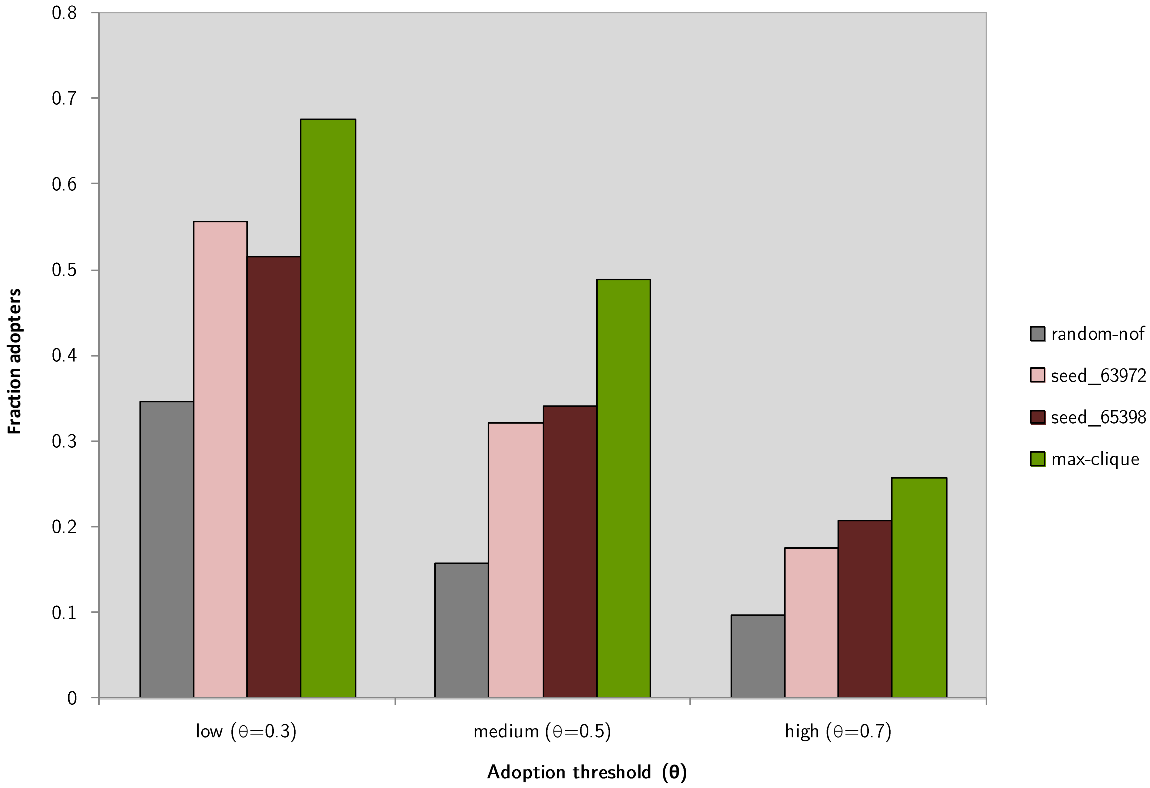


Table S21

Results from additional experiments using a brute force method: effect of varying thresholds (θ) on fraction of switched agents[1] for two seeds that were filtered out in a previous step as those ones maximizing the overall fitness



Threshold	Random-nof		Seed_63972		Seed_65398		Max-clique	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Low (θ = 0.3)	0.347	0.116	0.557	0.028	0.516	0.018	0.676	0.038
Medium (θ = 0.5)	0.157	0.061	0.320	0.017	0.341	0.010	0.488	0.065
High (θ = 0.7)	0.096	0.037	0.175	0.008	0.207	0.003	0.256	0.021

[1] Average results for 100 simulation runs

Within additional experiments I pursued the objective to find one combination of agents (from the large number of all possible combinations) that maximized the overall diffusion outcome in the network. As a first step, I decided to limit attention to cases in which the number of agents was restricted to eight as this was the size of the maximum clique – my target that I aimed to outperform. Then, I generated five sets of seeds with either 10,000 or 100,000 combinations, overall 320,000 combinations. Then, I used Behavior Search – an extension for the simulation environment Netlogo – as a means to find those combinations that maximized the expected outcome. For each seed file (a text file with 10,000 or 100,000 combinations), I performed five searches to ensure that I find a well performing solution.

The subsequent figure shows the Behavior Search interface for one sample run with five searches. In particular, I drew on a genetic algorithm that aimed to maximize the overall fitness. As my outcome measure, I chose the fraction of switched agents after one shock. Results are depicted in the previous table for two seeds that performed best.

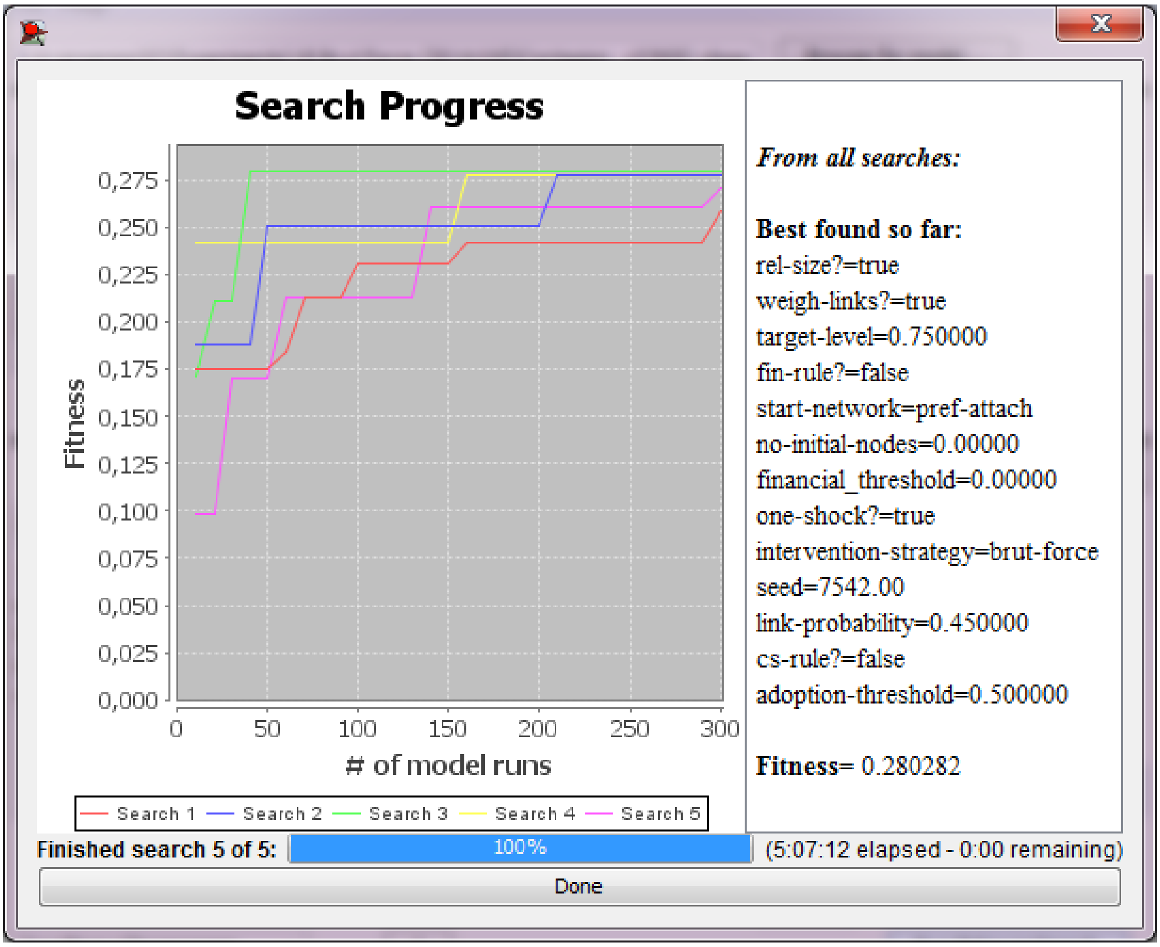
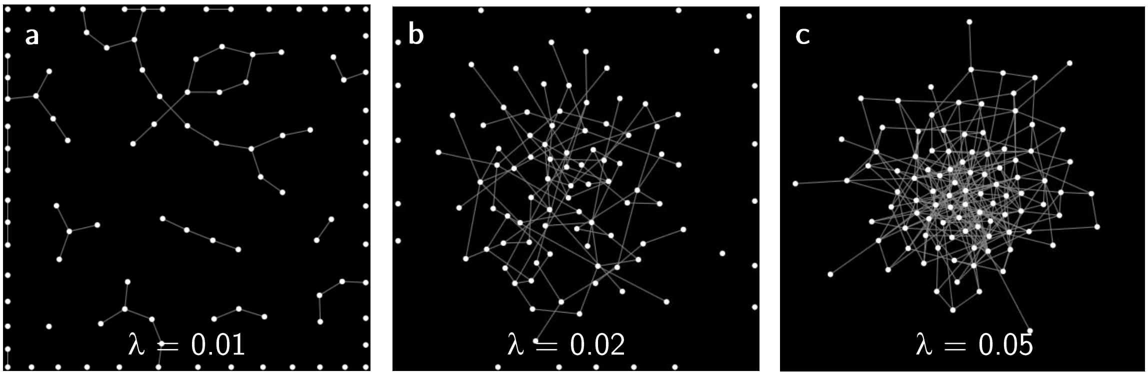


Table S22

Experimental results for theoretical network structures

I performed experiment on different theoretical network structures to see whether the system was converging to the target level (75% of the population) and how many shocks where necessary to achieve that level. First, I turn to random networks. As (Poisson) random networks are well understood analytically, they serve as a useful baseline to characterize important properties of my model (cf. Jackson 2008b:9-14). Each link between nodes is formed with a given probability *p*. In such network, a connected component – where all nodes in the network can be reached via paths – arises if the probability of a link forming is larger than log(n)/n (cf. Erdös and Rényi 1961; Jackson 2008b).

I initialized a static random network with n = 100 nodes and varying link probabilities (λ). In this network, I expect that a giant component will arise at log(100)/100 = 0.02. As expected theoretically, we see a sparsely connected network with several disconnected islands in figure (a) for λ = 0.01. For λ = 0.02 in figure (b), a giant component emerged; though some isolated nodes remained. For λ = 0.05 in figure (c), the network was having a giant component and the entire network was almost surely connected.



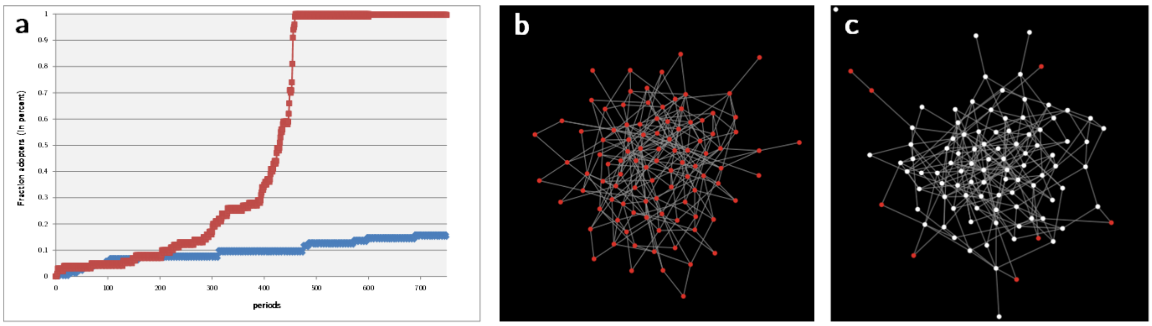
Using the network analysis algorithm (refer to **Algorithm A.8**) and fixing the simple threshold to a medium level (θ = 0.5), I performed simulations triggering one node uniformly at random at a time and tracking the subsequent domino effect running through the network. Multiple interventions were performed until the network exceeded the target level or until the time limit of the simulation (5,000 ticks) was reached.

The subsequent table shows results. For disconnected random networks (λ = 0.01), the network did not converge to the target level and the system plateaued at a level around 50 percent of adopters. I observed that many interventions did not impact the network as they targeted isolated nodes that could not trigger subsequent cascades. For random networks with medium degrees of connectedness (λ = 0.02), we see that the network exceeded the target level in most cases whereas about one-third of all nodes had to be shocked before the system converged. The most salient feature for completely connected networks (λ = 0.05) is the high standard deviation in the number of shocks until convergence. This is due to the fact that many simulations failed to tip enough nodes to exceed the network within the time limit. In these cases, the network plateaued at a lower level of adopters as the standard failed to spill over from few nodes in the periphery to the core.

	Number shocks[1,2,3,4]		Fraction adopters (in percent)	
	Mean	Std. dev.	Mean	Std. dev.
random ($\lambda = 0.01$)	n/a	n/a	0.49	0.07
random ($\lambda = 0.02$)	35.71	12.68	0.83	0.05
random ($\lambda = 0.05$)	1917.25	2299.39	0.70	0.39

[1] Average results for 1,000 simulation runs
[2] Reports the number of shocks until the network converged to the target level (0.75)
[3] Time limit was set to 5,000 ticks
[4] *n/a* denote cases where the network did not converge to the target level

The subsequent figure (a) captures how dynamics enfolded in cases where the standard spilled over (figure b) and where it failed to gain momentum (figure c). We performed additional simulations for higher link-probabilities but I found that the system did not converge for link-probabilities larger than $\lambda = 0.05$. These results indicate that the higher average degree of each node in these networks created a counteracting effect that restricts the diffusion of the standard in these networks.



I turn to further theoretical network structures. First, I performed additional simulations for lattices and for star networks. The subsequent table shows results. Lattices have a regular structure and each node is either surrounded by two, three or four neighbors based on the positioning in the grid. As shown in the table, for lattice networks the system did not converge as each intervention failed to trigger a subsequent cascade for a medium threshold ($\theta = 0.5$). Next, I turn to star networks. Stars have a very centralized structure with one node in the center that is connected to any other node in the network. As shown in the table, I found that the number of shocks varied widely based on the random period in which the center node became shocked. I then observed that the system converged immediately to a completely standardized state in which any node in the network adopted.

In a next set of experiments, I turn to preferential attachment networks. The table shows results. We see that the system converged in almost any case to a state of complete adoption. As the preferential attachment network is completely connected, all of the nodes reside within one giant component. The hub-and-spoke structure further fosters the diffusion as the standard can progress from the periphery to the center of the network. Viewed together with the previous table, I can thus conclude that the structure of the network fosters the diffusion of the standard. With respect to the number of necessary shocks, a random network with medium connectedness ($\lambda = 0.02$), however, outperformed the preferential attachment network as the tipping point was more pronounced in these networks.

	Number shocks[1,2,3,4]		Fraction adopters (in percent)	
	Mean	Std. dev.	Mean	Std. dev.
Lattice2d	n/a	n/a	0.01	0.00
Preferential attachment	39.13	9.83	0.99	0.02
Star	97.57	91.04	1.00	0.00

[1] Results averaged over 1,000 simulation runs
[2] Reports the number of shocks until the network converged to the target level (0.75)
[3] Time limit was set to 5,000 ticks
[4] *n/a* denote cases where the network did not converge to the target level

Declaration of Authorship

Excerpt where reference is made in the text of this thesis, this thesis contains no material published elsewhere or extracted in whole or in part from a thesis presented by me for another degree or diploma. No other person's work has been used without due acknowledgement in the main text of the thesis. This thesis has not been submitted for the award of any other degree or diploma in any other tertiary institution.

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Date *Signature*