

Innovation and Breaching Strategies in Multi-Sided Platform Markets: Insights from a Simulation Study

Completed Research Paper

Gorkem Turgut Ozer

University of Texas at Austin
McCombs School of Business
Austin, Texas, United States
gtozer@utexas.edu

Edward G. Anderson Jr.

University of Texas at Austin
McCombs School of Business
Austin, Texas, United States
Edward.Anderson@mcombs.utexas.edu

Abstract

This study explores how multi-sided digital platforms achieve and sustain superior performance positions in turbulent markets. Specifically, the effects of three major strategies are studied: (1) a complementarity-based innovation strategy, (2) a breaching strategy where a platform expands into rival territories by introducing its offerings in rival platforms to gain access to rivals' consumers without having to switch them over, (3) the joint use of these strategies. Multi-sided platform markets tend to exhibit turbulence; hence, platform strategies need to focus on achieving and sustaining superior performance positions for longer periods. We use agent-based simulation models to show that innovation and breaching strategies contribute to platform performance. Multi-sided platforms that pursue a breaching strategy in addition to engaging in innovations achieve higher performance positions than those that only engage in innovations. Our analyses also generated insights about the importance of a fit between the decision rules that platforms follow in implementing their strategies and consumer decision structures.

Keywords: Multi-sided digital platforms; Digital business strategies; Agent-based modeling

Introduction

Firms increasingly embrace the platform marketplace idea by either transforming their businesses into platforms or creating new platforms (Hagiu, 2007). Multi-sided platforms are businesses that enable transactions among different sides (e.g., between consumers and developers) without taking ownership and control over products (Hagiu & Wright, 2013). Prominent firms such as Google, Apple, and Amazon have adopted platform models in their businesses. For example, Google's search business is a multi-sided platform where consumers transact with content providers and advertisers. Similarly, the core of the Apple's mobile business, iOS App Store is a multi-sided platform where consumers transact directly with application developers. These multi-sided digital platforms differ from traditional businesses in various ways such as by the strength of network effects and switching costs, governance and pricing structures, and product designs (Anderson, Parker, & Tan, 2014; Armstrong, 2006; Caillaud & Jullien, 2003; Gawer, 2009; Hagiu & Spulber, 2013; Parker & Alstyne, 2005; Rochet & Tirole, 2006; Venkatraman & Lee, 2004).

In multi-sided platform markets, constantly changing needs and preferences on the consumer side and frequent new offerings on the platform and complementor side lead to dynamic interactions and interdependencies. We show that these interactions and interdependencies are nonlinear, leading to increasing complexity (Cilliers, 2000; Page, 2009). In turn, complexity leads to increasing turbulence and unpredictability in markets in which performance rank orderings of firms change and fluctuate in high degrees (D'Aveni & Gunther, 1994), product cycles are short and competitive landscapes rapidly shift in

unforeseen ways (Eisenhardt, 1989). In these markets, leading firms are constantly pursued by challengers that aggressively find new ways to destroy the competitive advantage of the leaders (D'Aveni, Dagnino, & Smith, 2010); hence, platform strategies need to cope with these dynamisms. We identify and conceptualize a platform fitness¹ strategy to extend the scope of competitive strategies in platform markets such as expansion strategies (Hagiu, 2006), standards setting (Boudreau, 2010; West, 2003), pricing and foreclosure strategies (Eisenmann, Parker, & Alstyne, 2006; Eisenmann, Parker, & Van Alstyne, 2011).

This study seeks to contribute to the literature on multi-sided platform markets in two ways. First, the study seeks to discuss how complexity emerges in multi-sided platform markets from the interactions and interdependencies among consumer actions and platform offerings, and how it leads to a high level of turbulence and unpredictability in these markets. Second, the study seeks to examine the effects on platform fitness levels of (1) a complementarity-based innovation strategy, (2) a new kind of strategic penetration into rival platform markets, –breaching–, which contributes to fitness by evoking and enhancing exploratory learning, and (3) the joint use of these strategies. We take a complex adaptive systems perspective to study these strategies, more specifically, to study the interaction effect resulting from the joint use of both the innovation and breaching strategies. We build on and extend the theories on organizational fitness in complex adaptive ecosystems to embrace exploratory learning and innovation. The importance of learning and the need for exploratory and experiential learning when existing knowledge offers little insight are hardly controversial (e.g., March, 1991; McGrath, 2001). However, how exploratory learning can be prosecuted in the platform strategy context, and how such a strategy can translate into higher performance levels on a complex fitness landscape are not nearly so well understood. We show in turbulent and unpredictable platform markets that achieving and renewing performance advantages are constant struggles, and that complementarity-based innovation and breaching strategies positively contribute to platform performance. More specifically, platforms that employ the breaching strategy in addition to engaging in complementarity-based innovations achieve the best results. This result extends the theories of fitness in complex adaptive systems to multi-sided platform markets by describing how exploratory and experiential learning could be pursued as a platform strategy to achieve higher fitness levels, and how such a strategy can affect platform performance through complementarity-based innovations. Finally, our model offers insights about the importance of a fit in these markets between the decision rules that platforms follow in implementing their strategies and consumer decision structures.

Theory and Hypotheses

The emergence of platform businesses has triggered a shift in competition from the conventional product-level competition to a new, platform-level competition (Eisenmann et al., 2006; Hagiu, 2006; Zhu & Iansiti, 2012). Platform-based firms compete not only on individual products but also as platform ecosystems. They are composed of a large set of diverse agents interacting with one another in nonlinear ways. For example, Apple's iOS and Google's Android OS platforms compete with each other as platform ecosystems over which thousands of developers offer millions of applications to billions of consumers (Statista, 2014). On the consumption side, these platforms compete for consumers and seek to become a single-stop shop for all their information and entertainment needs (Yoffie & Rossano, 2012). On the production side, they compete for complementors (e.g., application developers, content providers) and try to convince them to participate in their platforms (Boudreau, 2012). By making connections to millions of consumers and complementors, these platforms seek to create direct and indirect network effects, and increase switching costs in their favor (Eisenmann et al., 2006; Evans, 2003; Rochet & Tirole, 2003). As they compete for the same pool of consumers and complementors, interdependence increases. That is, if one platform performs well by attracting consumers and complementors and locking them in, rival platforms perform poorly. Consider the usually two-sided internet browsers market (i.e., consumers at one side and add-on developers at the other side). Figure 1 shows how frequently and significantly performance rank orderings have changed in this market². In just five years, Chrome has emerged as the market leader, Internet Explorer and Firefox lost significant market share. In addition to having interdependent performance levels, platforms are diverse, adaptive, and connected. These characteristics define complex adaptive systems (Cilliers, 1998).

¹ Fitness refers to the performance in achieving positive payoffs during the course of interactions (Holland, 1995; Siggelkow, 2001).

² In Figure 1, even though the market leader changed once, there are ten rank ordering changes in total.

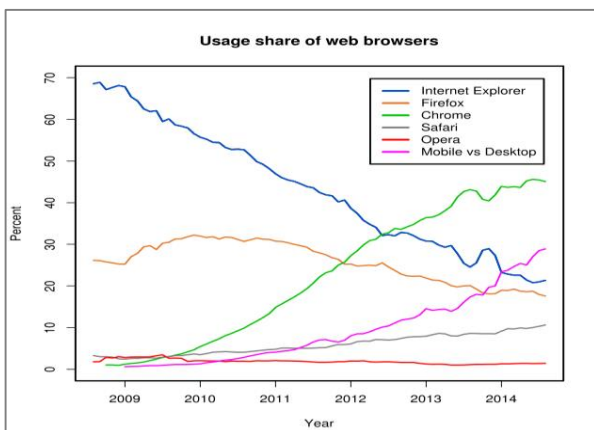


Figure 1: Share of global usage of end users for internet browsers (StatCounter, 2014)

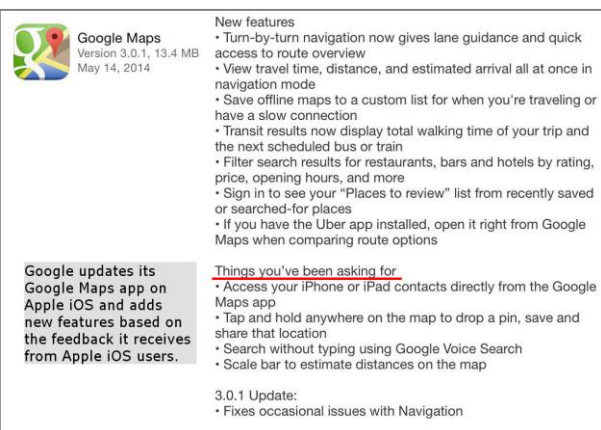


Figure 2: A screenshot of the Google Maps update on Apple iOS device iPad (2014)

Multi-sided Platform Markets as Complex Adaptive Systems

Frequent and significant performance rank ordering changes in multi-sided digital platform ecosystems are a likely consequence of complexity in these ecosystems. Scholars of complexity inform us that *moderate levels* of (1) diversity, (2) adaptation, (3) connectedness, and (4) interdependence among the agents in an ecosystem lead to complex adaptive systems (Cilliers, 1998; Page, 2009). Complex adaptive systems are formed by a large number of agents whose nonlinear interactions lead to continual flux and uncertainty (Holland, 1995). When agents in an ecosystem exhibit low levels of diversity, adaptation, connectedness, and interdependence, the system is simple or complicated. When agents exhibit high levels of these characteristics, the system is chaotic. An essential difference between a simple or complicated versus a chaotic system is that the former systems are decomposable into their parts; however, the latter is not. The behaviors of decomposable systems can be inferred from its parts. Social systems are not decomposable, and at best they are nearly-decomposable (Cilliers, 2001). That is, in complex adaptive social systems, the system-level behavior can be very different from the behaviors of individuals or agents (Simon, 1962):

Roughly, by a complex system I mean one made up of a large number of parts that interact in a nonsimple way. In such systems, the whole is more than the sum of the parts, not in an ultimate, metaphysical sense, but in the important pragmatic sense that, given the properties of the parts and the laws of their interaction, it is not a trivial matter to infer the properties of the whole. (p. 468)

Accordingly, the fitness landscapes³ that correspond to simple or complicated —i.e., decomposable— systems may have a single peak or a series of peaks, constituting a rugged landscape (Page, 2009; Rivkin, 2000). Given enough time and resources, the outcomes in these landscapes can be maximized by incremental search. Complex adaptive systems, however, constitute dancing rugged fitness landscapes (Kaufmann, 1993; Levinthal & Warglien, 1999), and they require nonincremental search and exploration. This is because these landscapes constantly morph and the peaks on them collapse or emerge accordingly. Our development below indicates that multi-sided platform markets form complex adaptive systems.

Diverse and Adaptive. *Multi-sided platforms are moderately diverse.* They use similar structures and offer similar features and services, but they are also diverse and differentiated. Platforms have digital infrastructures, technology standards and business rules that seek to solve a common problem for their stakeholders: e.g., users, third party developers, advertisers, or content providers. Consider Apple iOS and Google Android OS. As individual platforms make decisions on infrastructure, technology standards, and business rules, mimic and copy one another's capabilities, they contribute to the emergence of similarity in the industry. However, they have differences in their decisions (e.g., open versus proprietary standards, compatible versus incompatible technologies, business models that emphasize device sales vs. advertising revenues and fees, etc.). *Multi-sided platforms are also moderately adaptive.* They invest in technologies,

³ An important concept in this regard is the notion of a fitness landscape introduced by Wright (1931, 1932). In such a landscape, fitness is a measure of how successfully agents move from “fitness valleys” to “fitness peaks.” Organizations aim higher fitness by migrating toward peaks (Rivkin & Siggelkow, 2002).

standards, and business rules to increase their capacity to adapt to environmental changes. For example, they digitally track and analyze behaviors of their consumers, complementors, and rivals, and adjust their actions accordingly. They develop intelligent responses to competitive moves of rivals and meet changing consumer needs and preferences. However, even with superior capabilities, platforms are not fully adaptive to the dynamically evolving environment. For example, in gaming platforms market, PlayStation and Xbox platforms better adapted to the changes in user behavior in online social networks by adding extensive social interaction features than Nintendo's Wii platform, which, could not adapt to these changes.

Connected and Interdependent. *Multi-sided platforms are moderately connected to one another.* Because they compete for the same pools of consumers, complementors, and advertisers, and use similar types of technologies, standards, and business rules, they are connected to one another through these stakeholders and tools. Because most of their processes and interfaces are digitized, the connections among platforms are established easily. For example, similar application programming interfaces (APIs) offered to encourage independent parties to develop complementary offerings increase connectedness. *Multi-sided platforms are also moderately interdependent.* They have various dependency relationships with their rivals (e.g., manufacturing, supply, distribution, marketing agreements, and joint ventures) and with their consumers (e.g., marketing, advertising, services). APIs also contribute to the interdependency of platform-based competitors because they tend to use similar standards. Multi-sided digital platforms are interdependent also because they compete for the same pools of consumers and complementors.

In addition to the complexity arising from the composition of platform markets, we argue that network effects and switching costs contribute to complexity, thereby increasing turbulence and unpredictability.

Network Effects as a Source of Complexity

Network effects in the form of network externalities have been extensively studied in the networks literature (Fuentelsaz, Maicas, & Polo, 2012; Shankar & Bayus, 2003; Zhu & Iansiti, 2007, 2012). Because multi-sided platforms compete with each other both for consumers and for complementors, there are network externalities on both the production side and the consumption side (Gandal, 1995; Venkatraman & Lee, 2004). From a game theory perspective, network effects arise from scale economies; i.e., the available surplus per consumer increases with the increasing size of a consumer base or with the increasing amount of offerings by complementors on a platform due to scale advantages. These sources of scale advantages define direct and indirect network effects. In case of *direct* network externalities, consumers benefit more from a platform as the quantity (and quality) of consumers who adopt the platform increases (Katz & Shapiro, 1985). In case of *indirect* network externalities, consumers benefit more from a platform as the quantity (and quality) of complementary offerings on the platform increases (Gandal, 1995). Therefore, network externalities are likely to contribute to lock-in of consumers to platforms when they are positive (Farrell & Klemperer, 2007). Network externalities bring multi-sided platform markets increasing diversity, connectedness, and interdependencies of the constituents. As the network size and strength⁴ increase, the potential utility consumers can gain from a platform increases. The increased attractiveness brings in more consumers, and hence more developers, advertisers and other complementors on one hand; increases the complexity on the other hand. Increased network externalities attract even more consumers, which in turn is likely to increase network externalities. These feedback loops and increased connectedness and interdependencies of nonlinearly interacting diverse constituents of an ecosystem lead to increasing complexity, thereby increasing the turbulence and unpredictability in platform ecosystems.

Switching Costs as a Source of Complexity

Switching costs can arise from various sources. The cost can be procedural (economic risk, evaluation, learning, setup costs), financial (benefit loss, monetary loss costs), or relational (personal relationship, brand relationship costs) (Burnham, Frels, & Mahajan, 2003). Like network effects, switching costs arise because consumers desire compatibility. That is, consumers want a group of their purchases to be compatible with one another, creating economies of scope among purchases on a single platform (Farrell & Klemperer, 2007). Consumers face significant switching costs when their investments specific to a platform decrease in value or become obsolete after they switch to another platform. For example, consumers spend

⁴ The quantity of connections defines the size of a network and the quality of connections defines the strength of a network. These two dimensions together denote a measure for the network externalities.

time and other resources to learn how to use an adopted platform and accumulate platform-specific application data on the platform. If consumers switch to another platform, they are incurred additional costs to learn how to use a new platform, invest in a new set of complementarities that are compatible with the new platform, and port their data to the new platform. These costs play a significant role in switching decisions (Teece et al., 1997), and switching costs contribute to consumer lock-in (Fuentelsaz et al., 2012).

If there are both strong network effects and significant switching costs, consumer lock-in is more likely in a platform ecosystem, as evident in the winner-take-all phenomenon (Eisenmann, 2007; Sheremata, 2004). If there are not significant switching costs, however, network externalities may not provide a strong enough incentive to lock in consumers. In the telecommunications industry, for example, despite strong network externalities harnessed by mobile operators, consumers tend to switch as soon as phone number portability is introduced (Fuentelsaz et al., 2012; Viard, 2007). Similarly, consider Groupon, a deal-of-the-day website that features discounted gift certificates and coupons. As more consumers sign up and shop at Groupon.com, Groupon offers better-priced deals. Therefore, indirect network externalities are present. There are also product and service reviews by consumers, creating direct network externalities. In fact, Groupon's network has the strongest network effects by network size as the firm holds the largest share in the deal-of-the-day market (Statista, 2013). However, Groupon's competitors, led by LivingSocial, did not have any struggle to attract its consumers because switching costs were lacking. Consumers switched to competitors easily, or used Groupon and its competitors at the same time, a phenomenon called multi-homing. When consumers in a market increasingly switch between competitors, and switch between single-homing and multi-homing decisions, nonlinear interactions and interdependencies among consumers, complementors, and platform providers are likely to increase, giving rise to complexity in the market.

Competition in Complex Adaptive Platform Ecosystems

In multi-sided digital platform markets where “winner-take-all” is not the outcome, the compositional characteristics of market constituents (i.e., diversity, adaptiveness, connectedness, and interdependence), the presence of network effects, and lack of significant switching costs lead to complex adaptive ecosystems. In these complex systems, cause-effect relationships are not proportional. Unexpected and unintended consequences, or surprises, are the expected behaviors of the system (McDaniel, Jordan, & Fleeman, 2003). In a complex adaptive system, system-level behaviors are emergent and unpredictable, and they are different from the behaviors of the individual parts that make up the system (Holland, 1995; Simon, 1962). Increasing complexity leads to turbulent changes in the fitness landscape of the industry (Eisenhardt & Martin, 2000), where turbulence denotes both the magnitude and frequency of the changes (Miller, Ogilvie, & Glick, 2006; Wholey & Brittain, 1989). Peaks that represent high performance positions in the industry's fitness landscape could collapse unexpectedly and unpredictably. Brand new peaks could emerge. The topography of the competitive landscape starts to dance and morph. Individual platforms face major challenges in achieving and sustaining higher fitness levels because of the difficulty in repositioning to emerging performance positions (Tanriverdi, Rai, & Venkatraman, 2010). As incumbents fall from their performance positions and other platforms take over the emerging peaks, performance rank orderings of the platforms change in unexpected ways. Multi-sided platforms that fall from high performance positions continuously attempt to move back up to peak performance positions and in the process disrupt the current occupants, and contribute to a constant state of disequilibrium and turbulence in performance rank orderings of all competitors (D'Aveni et al., 2010; D'Aveni, 1995; Wiggins & Ruefli, 2005).

Platform providers need strategies that can cope with the increasing complexity, turbulent and unpredictable changes in the fitness landscapes of platform ecosystems (Brown & Eisenhardt, 1998; Levinthal, 1997). One way to achieve higher fitness levels in these turbulent ecosystems is to engage in exploratory and experiential learning, which involves increased variation by search, experimentation, and innovation (March, 1991). Absent a base of cause-and-effect understanding, exploration and experimentation generates information that cannot be obtained by any other way (McGrath, 2001). The concept of exploratory learning translates into fitness landscapes as learning from a mix of short and long jumps. Platform providers should engage not only in neighborhood search as in the form of local “hill climbing” (Holland, 1975; March & Simon, 1958) but also in long jumps, which are the random explorations of the distant portions of a landscape (Kaufmann, 1993; Levinthal & Warglien, 1999). The importance of learning and the need for exploratory and experiential learning when existing knowledge offers little insight are hardly controversial (e.g., March, 1991; McGrath, 2001). However, how exploratory and experiential learning could be pursued as a strategy, specifically in the context of multi-sided platform markets, and how

this strategy could be transformed into higher performance levels in a complex fitness landscape are not nearly so well understood. We focus on three strategies and their effects on fitness levels to contribute to the literature in these areas: (1) a complementarity-based innovation strategy, (2) a breaching strategy that involves a novel way to expand strategically into a rival platform territory, and (3) a strategy that involves the joint use of the innovation and breaching strategies. We recognize the well-established contribution of an innovation strategy to firm performance and extend it by discussing the critical importance of complementarities in multi-sided platform markets. We also conceptualize a new strategy, breaching, and study its role in supplementing the complementarity-based innovation strategy in its fitness contribution.

Complementarity-based Innovation Strategy

As the complexity of a competitive landscape increases, platform providers face increasing levels of variety in needs and preferences of consumers and complementors such as independent developers and advertisers. When the external variety on an adaptive biological or social system exceeds the internal variety of the system, there emerges an adaptive tension (McKelvey, 2001). As Ashby's law of requisite variety states, only variety can absorb variety (Ashby, 1958; Beer, 1979, 1981). That is, to ensure its integrity and survival, a system must be adaptive, and must increase the variety of its internal order to match the variety imposed by its environment. Thus, one major competitive strategy in coping with the external complexity and the variety of multi-sided platform markets is to increase the internal variety of a platform (Boisot & McKelvey, 2010). However, how the internal variety is increased is also important. Internal variety can be increased by launching new exploratory offerings (March, 1991) or by launching new exploratory but at the same time complementary offerings and configuring them into the current bundles of offerings (Lee, Venkatraman, Tanriverdi, & Iyer, 2010). The more innovative and complementary offerings on a platform, the more likely the platform is to meet the needs and preferences of the participants. Not surprisingly, prominent mobile platforms, such as Apple iOS and Google Android OS, for example, offer millions of applications. They also focus on certain types of complementarity relationships, such as in the case of email, calendar, contacts, and tasks by Google. An innovation-based strategy is consistent with the prevailing explanation for turbulence in environments such as with Schumpeter's explanation that innovation-based competition for product markets creates a state of constant disequilibrium (1942), as innovative entrants make frequent, aggressive, and unforeseen moves to disrupt incumbents (D'Aveni & Gunther, 1994).

Product-based innovations are not sufficient in platform-based competition. Innovations must complement existing offerings to increase fitness of a platform because the consumers of the platform adopt the innovative applications as a complementary set to benefit from the economies of scope (Farrell & Klemperer, 2007). Therefore, our emphasis in this study is on a platform's strategy to introduce complementary innovations on the platform, but not the isolated disruptions at the product level. Only innovations that are complementary and that promise compatibility could attract consumers who seek for network externalities (Gandal, 1995). Increased complementarity relationships among the offerings that the consumers of a platform adopt are likely to increase switching costs for the consumers when these relationships are platform-specific, creating lock-in effects. Similarly, network externalities increase and make a platform more attractive for other consumers due to the increased use of the complementary offerings that are compatible with the platform. The diversity in the needs and preferences of consumers could only be matched by increasing the internal variety, thereby creating a repertoire of offerings that are at least as nuanced as the needs and preferences of consumers. However, as product-level innovations may not be sufficiently effective at the platform-level to create the desired network externalities and switching costs, hence locking in consumers to control turbulence and unpredictability arising from complexity, we argue that platforms need to engage in complementarity-based innovations to achieve higher fitness.

Hypothesis 1: *Multi-sided platforms that engage in a complementarity-based innovation strategy are more likely to achieve higher performance levels than the rival platforms that do not employ this strategy.*

Breaching Strategy

Multi-sided platform markets as complex adaptive systems provide a challenge for the traditional, routine-based organizational learning where organizations repeat the actions and strategies that were proven successful in the past, and stop repeating the actions that are associated with negative outcomes (Cyert & March, 1963; Lant, Milliken, & Batra, 1992). Two major mechanisms to update these cause-and-effect oriented routines, search and experimentation (Levitt & March, 1988), are rules rather than exceptions to

achieve higher fitness levels in complex adaptive systems. This is because cause-effect relationships are not linear, blurred, and complexity hinders learning from evidence (Sterman, 2006). Unintended consequences emerge as the constituents of a system interact nonlinearly and the outcomes aggregate in unexpected ways (Sargut & McGrath, 2011), leading to turbulence and unpredictability in fitness landscapes (Brown & Eisenhardt, 1998; Levinthal, 1997). These fitness landscapes are not only rugged but also dancing; therefore, nonincremental search and exploration are needed to increase the likelihood of achieving higher performance peaks as the landscape morphs (Kaufmann, 1993; Levinthal & Warglien, 1999). In multi-sided platform markets, breaching strategy, as we term it here, provides a novel way for platforms to engage in nonincremental search and exploration in the rival territories of a landscape. Behaving as if they are complementors to rival platforms, platforms that take breaching actions gain access to the rivals' turfs⁵. We recognize the potential effects of breaching in the form of direct fitness benefits such as in additional sales and advertising revenues (cf. Adner, Chen, & Zhu, 2014); however, we also argue that another primary benefit of a multi-sided digital platform from pursuing a breaching strategy is exploratory learning.

Breaching strategy evokes and enhances search and monitoring mechanisms of a platform provider that feed into exploratory learning (Huber, 1991; McGrath, 2001). An important concept in this regard is Wright's (1931, 1932) notion of a fitness landscape, or an organization's performance landscape (Levinthal & Siggelkow, 2001). In a complex adaptive system, the landscape characteristics, the height, shape, or location of peaks change, new peaks arise, and so forth (Siggelkow, 2001); therefore, intelligence is constantly needed in the landscape, not only in the neighborhood area of a platform but also in the distant parts of the landscape (Holland, 1975; March & Simon, 1958). Breaching allows platforms to collect valuable intelligence on the needs and preferences of consumers and complementors by taking a mix of short and long jumps, and exploring the distant parts in the landscape. Platforms that take breaching actions have the opportunity to engage in diverse interactions with the rivals' consumers and complementors and learn from them as they explore the landscape. For example, in the mobile platforms market, the engagement is through feedback and review mechanisms. Mobile platforms that use the breaching strategy receive a diverse set of feedback from the rivals' consumers. They also engage in a closer relationship with the rivals' complementors through the direct interactions with developer communities. The outcomes of these interactions increase internal variety through exploratory learning (March, 1991) and contribute to platform fitness (Levinthal, 1997). Figure 2 shows an example of learning from a rival platform's territory, in this case learning by Google from Apple's iOS consumers. As shown in the figure, Google improves its Google Maps application (app) based on the feedback provided by Apple's consumers through app reviews.

In the markets where turbulence and unpredictability are norms rather than exceptions, those organizations that prove to have superior exploration of the landscape are likely to adapt to changing circumstances better than their rivals (McGrath, 2001). Multi-sided digital platforms that employ the breaching strategy can better adapt to the changes arising from the changing consumer needs and preferences, and the rapid, significant, and unpredictable changes in network externalities and switching costs. The enhanced exploratory learning provides an opportunity to create the type of complementarity and compatibility relationships among a platform's offerings that are needed to match the needs and preferences of consumers. These platforms have an advantage in attracting consumers from rival networks because they learn from rival consumers to create the type of positive network externalities the consumers in the distant parts of the landscape desire the most. They manage the interdependencies and connectedness arising from network externalities more effectively. Using the breaching strategy also helps them manage the complexity arising from switching costs because they sense and make sense of the changes in rival territories. They pursue adaptations in their offerings accordingly and match the offerings of rivals to discourage switching out of their platforms. They create the types of barriers needed to keep consumers.

Hypothesis 2: *Multi-sided digital platforms that employ a breaching strategy are more likely to achieve higher performance levels than the rival platforms that do not employ this strategy.*

⁵ For example, Google, as a mobile platform provider itself (i.e., Android OS), offers applications on Apple's iOS mobile platform. Some of these applications such as Google Maps, Google Search, and Gmail are among the most popular applications on the iOS platform. From Apple's perspective, Google is seemingly a complementor at the product level; it is just another third party application developer. However, Google is also a competitor of Apple in the mobile platforms market, at the platform level.

The Joint Impact of the Innovation and Breaching Strategies

Breaching strategy evokes and enhances experimentation and experience-based mechanisms of a platform provider, outcomes of which feed into exploratory learning and learning-by-doing instead of learning-before-doing (Argote & Miron-spektor, 2011; Huber, 1991; Pisano, 1994). In complex adaptive systems, the key for achieving higher fitness levels is "to learn while in the middle of action; to think your way out while acting, and to act your way out while thinking" (McDaniel et al., 2003: 274) because successful learning is richly embedded in taking actions, not in considering consequences (March, Sproull, & Tamuz, 1991). The lack of cause-and-effect relationships in complex adaptive systems requires organizations to engage in trial-and-error experimentation and learn from this experience to achieve higher performance levels (Eisenhardt & Martin, 2000; Levitt & March, 1988). Pursuing a breaching strategy enables multi-sided platforms to expand their action spaces in a way that they go beyond "satisficing" learning points in their experiences (Rivkin & Siggelkow, 2002; Simon, 1979). These evolutionary searches create robustness and adaptability through constant experimentation (Beinhocker, 1999). We argue that experimentation through breaching actions using complementarity-based innovations contributes to *adaptability* rather than *adaptation* (Huber, 1991). This is because the value of exploratory searches through breaching actions in the form of a mix of short and long jumps over the landscape is leveraged by better-informed innovation episodes. A platform that employs a breaching strategy learns about emerging consumer needs and preferences on rival platforms as well as its own platform, and feed these insights into its new product development processes. Gaining access to emerging needs and preferences of consumers and complementors across the landscape enables a platform to cast its innovation web wide, facilitating the absorption of a broader scope of variety from the landscape (Beer, 1979, 1981). This competitive intelligence complements the innovation processes, enabling platforms to offer products that align better with emerging needs and preferences of consumers.

Accordingly, we argue that the outcomes of a breaching strategy are likely to complement and positively reinforce the effects of a complementarity-based innovation strategy. This is because the effectiveness of an innovation strategy is contingent on the competitive intelligence on the emerging needs and preferences of consumers, which we refer to as the need for requisite variety (Ashby, 1958; Beer, 1979, 1981). Breaching strategy helps platforms selectively respond to the massive variety it confronts (Boisot & McKelvey, 2010). A platform that engages in an innovation strategy, but not in breaching can develop insights about the needs and preferences of consumers and complementors on its own platform and in the neighborhood area (Levinthal, 1997; March, 1991). However, it does not have access to insights about the emerging needs and preferences of consumers and complementors in rival territories. Thus, it engages in local or incremental search for innovation, which is likely to end at a local peak closest to the starting point of the search process, regardless of its height relative to other peaks in the landscape (Levinthal & Warglien, 1999). However, given that the overall landscape is turbulent and unpredictable —thus, dancing as well as rugged—, searching and innovating only locally can make platforms vulnerable to changes elsewhere in the landscape while they settle down on "sticking" points which may not even be local peaks (Rivkin & Siggelkow, 2002). In addition, we expect a breaching strategy to increase the likelihood and effectiveness of learning from rare events and experiences (March et al., 1991). Taking long jumps allows platforms to break path dependencies and enables emergent learning based on rare experiences in the rivals' territories by creating divergent learning trajectories (Cohen & Levinthal, 1994; Lampel, Shamsie, & Shapira, 2009; Lampel & Shapira, 2001). Taking these long jumps in addition to local search also makes harder the imitation of innovation strategies by competitors (Beinhocker, 1999; Rivkin, 2000), increasing the likelihood of sustainability in higher fitness. Therefore, we posit that the positive impact of a complementarity-based innovation strategy will increase when combined with a breaching strategy, enriched and enhanced by the provided intelligence.

Hypothesis 3: *Multi-sided platforms that employ a breaching strategy in addition to engaging in complementarity-based innovations are more likely to achieve higher performance levels than the rivals that engage in only complementarity-based innovations without employing a breaching strategy.*

Modeling Multi-Sided Platform Markets

We use a computer simulation to model platform-based competition and test our propositions. Computer simulation is an increasingly significant methodological approach to theory development in organizational studies (Davis, Eisenhardt, & Bingham, 2007; Nelson & Winter, 1977) and fits the objectives of this study well because of the following reasons. First, nonlinear dynamics that characterize the multi-sided platform ecosystems are not mathematically tractable; therefore, a computer simulation is more appropriate (Arthur, 2013; Carley, 2005 in Baum, 2005). Second, computer simulations can reveal the outcomes of interactions

and interdependencies among strategic agents that unfold over time (Repenning, 2002). Third, computer simulations provide an effective research method for answering "what if" questions and moving beyond the current assumptions and theories (Romme, 2004). Finally, this research strategy provides insights into complex relationships that might not otherwise be possible to analyze due to data limitations (Zott, 2003). For these reasons, we designed an agent-based model (ABM), and carried out "computational experiments" (Maguire & McKelvey, 2006) to measure fitness levels in platform landscapes (Siggelkow, 2001). Another advantage of ABMs is the control in manipulation and measurement of crucial variables (Conway, 1959).

We test the hypotheses posited in this paper in a model of the mobile digital platforms market. The agents in this simulation model are the platform providers and consumers. It is worth noting that we define only the simple rules these agents follow for their own benefits. We do not manipulate any system level variables in the model. System behavior and the outcomes of the model emerge from the interactions of the agents who follow the simple rules, which are defined based on theory and practice of platform-based competition. For the purpose of this study, we assume that whether applications are offered by platforms or independent developers does not affect the platform selection decisions of consumers. For consumers, utility is gained when their demand sets are matched on a platform. That is why independent application developers are not defined as separate agents in the model. Appendix A provides the detailed execution steps of the simulation model. In the developed simulation model, consumers aim to have consumption-side synergies. Choosing complementary application offerings, they minimize search, integration, interoperability, and compatibility costs, and maximize the ease of use. That is, consumers demand the value of the system to be greater than the sum of the values of the individual products, or to be super-additive (Tanriverdi & Lee, 2008). Because consumers demand a super-additive system of complementary products, platforms compete to be single-stop shops for consumers (Lee, Venkatraman, Tanriverdi, & Iyer, 2010). Platforms aim to benefit from sub-additive cost synergies at the production side by offering complementary products. They renew their offerings by imitating their rivals and offering new products. Only when they are in an experimental treatment, they engage in innovation and breaching bounded by performance constraints.

Model Assumptions and Agent Behavior

We assume that the market is an oligopoly with four platforms because the four-firm concentration ratios tend to be high in digital platform markets. For example, in the mobile platform, internet browser, and video game console markets, the four-firm concentration ratios are more than 90% (StatCounter, 2014; Statista, 2014, 2015). Platforms in the model are identical two-sided ecosystems with consumers and application (app) offerings. We assumed that there is no distinction for consumers about whether a platform offers an app itself or an independent developer offers the application on the platform. *Consumers* have demand sets and they make platform selection decisions. Over time, they add and remove applications to/from their demand sets. As the compositions of their demand sets and platforms' supply sets change, consumers reevaluate their platform selection decisions. They check the list of overlapping apps between their demand sets and a platform's offerings, and calculate a utility score for each platform. Consumers follow the same rules in all experimental conditions and aim to maximize their utilities; however, they are not rational utility maximizers. They are boundedly rational with limited cognitive capacity to process the information that is available to them (Alchian, 1950; Simon, 1955). At each step, a randomly⁶ determined number of consumers reevaluate their options (i.e., alternative platforms) and decide whether to switch to another platform. 80% of the time, consumers add a new random app to their demand sets (i.e., engage in exploration). 20% of time, they drop the app that provides the lowest contribution to their utility scores.

Platforms have supply sets and make decisions on application (app) offerings. Over time, they add and remove applications to/from their supply sets. 80% of the time, platforms add a new app to their supply sets. Platforms select the app to add by learning from their consumers. Platforms (1) read the demand sets of their own consumers, (2) identify the list of applications that are demanded by their consumers but not fulfilled yet, and (3) offer the app that is demanded the most. The most demanded app is *not* necessarily the app that makes a significant contribution to the platform's fitness level because platforms do not have perfect information to know which application would contribute to their fitness the most. Platforms aim to maximize their fitness; however, they are not the utility maximizers of the rational actor theory. They make application offering decisions on limited information and bounded by performance constraints. Platforms have both limited information and a limited capacity to learn and execute what they learn (March & Simon,

⁶ All randomizations in the model use the "random" function of Java's Math class (uniform distribution).

1958; Nelson & Winter, 1982; Simon, 1991). For these reasons, their decisions are suboptimal. 20% of the time, they drop the app that is demanded the least and that contributes to their fitness the least. This is because for application removal decisions, platforms own the information about the contribution of apps they already offer. The 80/20 ratio is based on empirical support. From the time Apple App Store was introduced until 2014, over 1.6 million apps have been introduced and 350 thousand apps have been pulled from the store (Adjust, 2014). That is, for 80 apps offered, approximately 20 apps are removed from the app stores. We tested the robustness of our results against this ratio as explained in the robustness analyses.

When platforms offer a new application (app) 80% of the time⁷, they do so in two different ways. 90% of the time, they imitate their rivals. In this case, they offer an app only if the app is already offered by a platform in the landscape. 10% of the time, they offer an app randomly (i.e., they engage in exploration). The way the platforms add new applications is diversified in two ways only to increase ecosystem dynamism. During the initialization of the model, platforms choose up to five apps to offer. If all platforms start by offering only a few apps and there is not an innovator platform (i.e., the experiment is a control setting without treatment), the number of apps remains stagnant. In this case, the behavior of the model is not a good representation of the reality and the data generated by the model are not useful. Because one of the ways to build a structurally realistic model is to make it comply with the characteristics and behaviors of the real system (Grimm et al., 2005), we allowed platforms to add an application 10% (of the 80%; thus, 8%) of the time randomly for exploration. Our results are robust to the rate at which platforms engage in this behavior. This rate affects only the number of times we need to run our model for consistent patterns.

Measures and Manipulations

Pairwise Complementarity Scores of the Applications

Pairwise product complementarities can be inferred from the extent to which consumers use the products together (Lemelin, 1982). Therefore, following the product-market approach (Brooks, 1995), it is possible to calculate pairwise complementarity scores based on the extent to which consumers use a pair of products together. In our model, pairwise complementarity scores are calculated using the number of consumers who use each app pair. In a given time period, the score of an app pair is calculated as follows:

$$\text{Let } x_{ijn} = \begin{cases} 1 & \text{if consumer } n \text{ uses apps } i \text{ and } j \text{ where } n = 1 \dots M \\ 0 & \text{otherwise} \end{cases}$$

$$\text{Then } p_{ij} = \frac{\sum_{n=1}^M x_{ijn}}{M} \quad (1)$$

where p_{ij} is the pairwise complementarity score between apps i and j , and M denotes the total number of consumers in the market. Pairwise complementarity between application pairs are assumed symmetric.

Consumer Utility Scores

Consumers make platform adoption and switching, and application removal decisions based on the utilities gained from the fulfilled portion of their demand sets. A consumer's utility is defined and calculated by the additive complementarity scores of the application pairs that consumers have in their demand sets and that are potentially fulfilled by a prospective platform. Therefore, consumers gain different amounts of utility from each platform in different time periods (as the compositions of demand sets and supply sets change). The utility a consumer gains from Platform A is calculated as follows:

$$u_n^A = \sum_{\substack{i,j \in A_n \\ i \neq j}} p_{ij} \quad (2)$$

where u_n^A is the utility of consumer n , A_n is the set of app pairs that consumer n has in its demand set and that are fulfilled by platform A, and p_{ij} is the pairwise complementarity score between apps i and j . Consumers adopt (or switch to) the platform that provides the highest utility; however, a stochastic multiplicative term is included in comparison of platform providers. That is, consumers make mistakes as

⁷ These offerings are not innovations, which are pursued only by the platforms treated in the experiments.

they compare utilities across platforms due to bounded rationality⁸. Among the platforms that provide the same utility to a consumer, consumers choose the platform with the highest number of other consumers:

$$\begin{aligned} \text{if } u_n^A &= u_n^B, & \text{select Platform A when } M^A > M^B \\ & & \text{select randomly when } M^A = M^B \end{aligned}$$

where u_n^A is the utility of consumer n from Platform A, u_n^B is the utility of consumer n from Platform B, and, M^A and M^B are the numbers of consumers on platforms A and B, respectively.

Platform Fitness Levels

We operationalized fitness levels using the economic theory of complementarities. The theory shows that a collection of products is complementary if the products have a real-valued utility function with increasing differences, or super-modularity (Topkis, 1998). Super-modularity is identified as super-additive value synergies where the joint values are greater than the sum of their standalone values (Tanriverdi & Venkatraman, 2005). Fitness levels are calculated by the weighted sum of pairwise complementarity scores of the all apps in the supply set of a platform, following an empirically validated approach (Lee et al., 2010):

$$f^A = \sum_{\substack{i,j \in \alpha \\ i \neq j}} \left[\frac{p_{ij}(\sum_{n \in C^A} x_{ijn})}{\sum_{n=1}^M x_{ijn}} \right] \quad (3)$$

where f^A is the fitness level of Platform A, α is the set of applications that is offered by Platform A, C^A is the set of consumers using Platform A, and p_{ij} is the pairwise complementarity score between apps i and j . The fitness level of a platform that employs the breaching strategy is calculated as follows:

$$f^A = \sum_{\substack{i,j \in \alpha \\ i \neq j}} \frac{p_{ij}(\sum_{p \in C^A} x_{ijp}) + \sum_{r \in C^B} x_{ijr})}{\sum_{n=1}^M x_{ijn}} \quad (4)$$

where f^A is the fitness level of Platform A that take a breaching action into Platform B, α is the set of applications that are offered by Platform A, C^A is the set of consumers using Platform A, C^B is the set of consumers using Platform B, and M is the number of consumers in the market.

Switching Costs

The sources of switching costs that are related to the consumer investments can be grouped into two categories: (1) breadth of use, and (2) extent of modification (Burnham et al., 2003). First, the breadth of use as a source of switching costs is defined as the extent to which a consumer employs a variety of products offered by a certain provider (Ram & Jung, 1990). As consumers buy complements and add supplements to the core product, the intrinsic retainability of the consumers increases (Blattberg & Deighton, 1996). Second, the modification of a product as a source of switching costs is defined as the extent to which consumers adapt the offered products so that they better serve consumers' individual needs (Burnham et al., 2003). As the amount of modifications on adopted products increases, switching costs increase because such modifications must be replicated upon switching providers (Bharadwaj, Varadarajan, & Fahy, 1993).

To measure the breadth of use in the mobile digital platforms context, we use the number of applications. As the number of applications consumers own on a mobile platform increases, switching costs related to the breadth of use also increase. A consumer who switches to another platform needs to create the same application complementarity relationships on the new platform. As the number of applications increases, this creation becomes more costly. To measure the extent of modification, we use time. As the time consumers spent on a mobile platform increases, switching costs related to the extent of modification also increase. As the time spent on a platform increases, the modifications on applications and porting of data accumulated in the applications become more costly because the extent of modifications and the amount of data accumulation are likely to increase over time. In the context we focus on, the number of applications and the time spent on a platform are likely to jointly increase learning costs as well. More applications used on a platform for longer periods tend to lock in consumers. Our model has a conditional decision criterion:

⁸ We did not limit the recognition of available platforms in the landscape, as there are only four platforms.

$$\text{Switch only if } t_n^P \frac{\beta_n^P}{\delta^P} < \frac{\sum_{n=1}^M t_n^P}{M} \frac{\theta_{in\ use}}{\theta_{supplied}} \quad (5)$$

where t_n^P is the time consumer n spends on the most recent Platform P . Every time a consumer switches to a new platform, the time is reset to 0. β_n^P is the number of apps consumer n owns on the most recent platform P , δ^P is the total number of apps available in the most recent Platform P 's supply set, M is the number of consumers in the market, $\theta_{in\ use}$ is the number of apps that are in use (at the calculation time) by all consumers in the market, and $\theta_{supplied}$ is the number of all apps that are offered by all platforms. Therefore, in a given time period, consumers are likely to subject to different amounts of switching costs.

Manipulated Variables

Innovation. We operationalized innovation as the introduction of new applications that are not available anywhere in the landscape yet. To innovate, platforms (1) read the demand sets of their own consumers, (2) identify the list of applications that are demanded by their consumers but not fulfilled by any platform in the landscape, and (3) offer the application that is demanded the most. If there is more than one application (app) that is demanded the most, platforms select among them randomly. The most demanded app is *not* necessarily the app that makes a significant contribution to the platform's fitness level because platforms do not have perfect information to identify the app that would contribute to their fitness levels the most. This is because complementarity scores are a function of the overall market demand, which is not visible to any platform in the landscape. Organization scholars inform us that organizations make decisions using limited information, and they have a limited capacity to learn and execute what they learn (March & Simon, 1958; Nelson & Winter, 1982; Simon, 1991). In other words, some innovations can (and do) fail in the model.

Breaching. To take breaching actions, (1) platforms read the demand sets of their own consumers, (2) identify the list of supplied applications that are demanded by their consumers but not offered by their rival with the highest number of consumers, and (3) offer the most demanded application to the rival platform that has the highest number of consumers. If there is more than one application that is demanded by the maximum number of consumers, platforms select one of these applications randomly to utilize it in their breaching actions. Offering the most demanded app in their own platforms may not provide platforms a significant enough fitness contribution. That is, breaching actions can (and do) fail in the model. The implementation of breaching decisions in our model is supported by the practice and theory of platform markets. Mobile digital platforms such as Google and Blackberry made statements confirming the rule we defined in this simulation model: *Offer applications only on rival platforms that have a large number of consumer base* (Vasile, 2014; Whittaker, 2012). The decision rule platforms follow in expanding to a rival platform with a large consumer base is also supported by the studies of network effects (Shankar & Bayus, 2003; Zhu & Iansiti, 2007, 2012). We operationalized breaching as a platform strategy to gain fitness benefits through exploratory and experiential learning by expanding into rival territories. Thus, platforms that employ the breaching strategy benefit in two ways. First, they learn from the consumers on target platforms by reading their demand sets (in addition to reading the demand sets of their own consumers; hence, exploratory learning)⁹. Second, the applications used in breaching actions can contribute to platform fitness levels through the adoption of these apps by the consumers on target platforms (see Equation 4).

Design and Analysis of Computational Experiments

To test the significance of the impact by the three focal strategies on fitness, we run the simulation model without any manipulated platforms (i.e., all platforms have the same conditions; control setting). Then, we enable one of the platforms to use the tested strategy, and run the simulation model again (i.e., treatment setting). In running simulation models, we take the averages for each period of the 200 periods in each simulation run. In other words, all periods ($t=0,1, 2, 3...199$) are repeated 200 times to increase reliability. Thus, 200 runs of a single time period generates only one observation. We run a two-sample Wilcoxon rank-sum (Mann-Whitney) test (i.e., rank-sum in Stata) to compare the fitness level of the manipulated platform in the treatment setting with its fitness level in the control setting. Wilcoxon Mann-Whitney test is useful to compare two settings and to test whether if one setting contributes more to higher ranked values.

⁹ At this point, it is worth noting that platforms cannot fully execute what they learn from these breaching actions. They rely solely on demand information in their decisions and the demand information per se does not guarantee the highest fitness contribution. This is because we know that organizations have a limited capacity to execute what they learn (March & Simon, 1958; Nelson & Winter, 1982; Simon, 1991).

It is more efficient than the t-test on non-normal distributions, such as a mixture of normal distributions, and it is nearly as efficient as the t-test on normal distributions. We collect the data on the performance level of a platform in the control setting and compare it with the performance level of the same platform in the treatment setting. Therefore, our experiments can be defined as within-subjects designs; however, because all platform providers in our model are identical, and random parameters generate independent subjects every time the model is run, our experiments can also be defined as between-subjects designs.

#	Control setting	Treatment setting	Comparison statistic Z score (Prob> z)	Probability that subject will perform better on the treatment than in the control ^a
A	Base setting (Imitation)	Innovation	z = -12.514 (0.0000)	86.2%***
B	Base setting (Imitation)	Breaching	z = -4.281 (0.0000)	62.4%***
C	Innovation (without Imitation)		z = -7.577 (0.0000)	71.9%***
D	Imitation and Innovation		z = -2.557 (0.0106)	57.4%*
<i>Sensitivity and Robustness Analyses</i>				
E	Imitation and Innovation <i>(Structural change: Consumers as rational actors)</i>	Breaching	z = -1.880 (0.0601)	55.4% [†]
F	Imitation and Innovation <i>(Structural change: Platforms as rational actors)</i>		z = 3.530 (0.0004)	39.8%***^b
G	Imitation and Innovation <i>(Structural change: Consumers and platforms both as rational actors)</i>		z = -3.108 (0.0019)	59.0%**

[†] $p < .10$ * $p < .05$ ** $p < .01$ *** $p < .001$

^a Probabilities in the original statistical test output are reversed (i.e., 1-p) and converted into percentages.

^b As the value is lower than 50%, breaching strategy has a negative effect on fitness in this experiment.

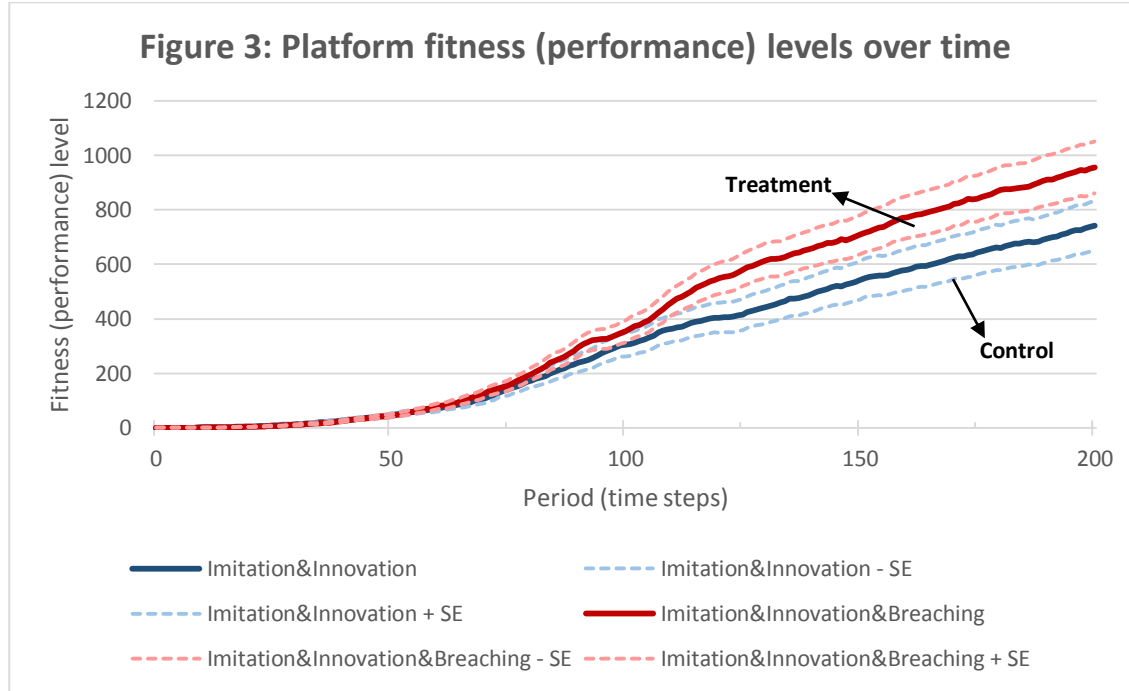
Table 1: Two-sample Wilcoxon (Mann-Whitney) test results for the experiments

Results

First, we tested whether the level of turbulence in our model follows our conceptual development and that in the empirical observations discussed earlier. We did not posit a hypothesis on turbulence; however, our theoretical development resided on the assumption of a turbulent, unpredictable market. This is why we calculated (1) the sum of average rank ordering changes, (2) number of times the market leader changes, and (3) probability that a platform sustains its performance level over time. The first measure shows how volatile the changes in performance positions (or fitness levels) in the market and it is calculated as follows:

$$\text{Sum of Average Rank Order Changes} = \sum_{t=1}^{200} \frac{\sum_{p=1}^P |Rank_t^p - Rank_{t-1}^p|}{P}$$

where $Rank_t^p$ is the rank order of Platform p at time t, and P is the total number of platforms. The second measure defines how many times the market leader is dethroned and is calculated by taking counts over periods. The results point to similar dynamics observed in the empirical instances such as in the internet browser or mobile platform markets discussed earlier. We found that the mean of the sum of average rank ordering changes in our simulation model is about 25, and the market leader is dethroned about 16 times in 200 time periods, on average. The probability that a platform sustains its performance rank ordering at least half of the time is found to be only about 15%. The probability is variable over time and has a positively skewed distribution with a median value of about 4.5%. Therefore, we conclude that the level of turbulence that emerges in our model is in accordance with our conceptual development and empirical observations.



* SE denotes standard errors, which is the standard deviation of the sampling distribution of the mean.

Figure 3: Platform fitness levels in *breaching, innovation, & imitation* vs. *innovation & imitation*

Our first hypothesis stated that multi-sided platforms that engage in complementarity-based innovations perform better than their rivals that do not employ the strategy. To test our first hypothesis, we compared the performance level of a platform in the control setting where it only imitates its rivals against the treatment setting where it employs a complementarity-based innovation strategy in addition to imitating its rivals. The results are shown in Table 1, Experiment A. The complementarity-based innovation strategy has a statistically significant positive effect on platform performance ($p < 0.01$). The effect is strong. 86.2% of the time, multi-sided platforms that engage in both complementarity-based innovations and imitations perform better than their rivals that only engage in imitations. This finding supports Hypothesis 1.

Our second hypothesis stated that multi-sided platforms that take breaching actions into rival territories perform better than their rivals that do not employ the strategy. Because our model includes only two strategies other than the breaching, we compared the performance effects of breaching strategy against these two strategies in Experiment B (breaching vs. imitation) and Experiment C (breaching vs. innovation). In Experiment B, we compared the performance level of a platform in the control setting where it only imitates its rivals against the treatment setting where it employs the breaching strategy in addition to imitating its rivals. The results are shown in Table 1, Experiment B. Breaching strategy has a statistically significant positive effect on platform performance ($p < 0.01$). 62.4% of the time, multi-sided platforms that employ the breaching strategy perform better than their rivals that only engage in imitations. In Experiment C, we compared the performance level of a platform in the control setting where it only engages in complementarity-based innovations against the treatment setting where it employs the breaching strategy in addition to engaging in innovations. Table 1 (Experiment C) shows that the effect is still positive, statistically significant ($p < 0.01$), and strong. 71.9% of the time, innovator platforms that use a breaching strategy in addition to pursuing complementarity-based innovations perform better than their rivals that only engage in complementarity-based innovations. Compared to the effect found in Experiment B, the breaching strategy has a higher contribution to platform fitness in Experiment C. This may be because the contribution of breaching actions is more critical in a market where a platform uses the learning from breaching in its innovation decisions rather than in its imitation decisions (see Hypothesis 3). By definition, innovation decisions include a novel offering that is not offered yet anywhere in the landscape. Therefore, innovation decisions bear more uncertainty than imitation decisions where offerings are already in use in other parts of the landscape. Breaching contributes more in managing the unpredictability arising from innovation decisions. Limited space prevented us from presenting more figures; however, in this setting,

breaching is effective earlier in the competition than it is in Experiment B. This may be because in a setting where a platform does not imitate others but only innovates, it starts to diverge from their rivals earlier.

Our third hypothesis stated that employing a breaching strategy positively reinforces the fitness effects of the complementarity-based innovation strategy. In Experiment C, we already showed that a platform that employs both the innovation and breaching strategies perform better than the control setting where it only engages in innovations. In Experiment D, we compare a platform in the base setting (i.e., imitation) that engages in complementarity-based innovations with the treatment setting where it employs both the complementarity-based innovation and breaching strategies. Table 1 (Experiment D) shows that breaching has a statistically significant positive effect ($p < 0.05$). Figure 3 shows a comparison of the performance levels in this setting. A close inspection of the figure reveals that after accounting for the standard errors, the effect is more salient later in the competition. There may be at least two reasons for this behavior. First, when a platform already imitates its rivals and innovates, it constantly introduces new offerings in two different forms. All these new offerings aim to attract consumers and increase its fitness levels. Thus, the likelihood of a marginal contribution to the platform performance earlier in the competition is likely to be lower. Second, as a platform imitates its rivals and innovates, it already interacts with a diverse set of consumers who switch in and out of its platform. The value in exploratory and experiential learning from the consumers of rivals could become valuable only after the rivals attract a significant number of consumers and consumers begin to move more slowly. Overall, multi-sided platforms that employ the breaching strategy in addition to the innovation strategy perform better 57.4% of time than their rivals that only engage in innovations. Experiment D provides support for Hypothesis 3, in addition to Experiment C.

Sensitivity and Robustness Analyses and Additional Insights from the Model

In this section, we evaluate whether our model reproduces the observed patterns robustly or whether our results are sensitive to changes in the model (1) *parameters* and (2) *structure* (Railsback & Grimm, 2011). First, we tested our model's sensitivity against the variance in our model *parameters* and found that our conclusions are robust to these variations. The initialization parameters are as follows: (a) the number of platforms ("4"), (b) number of consumers ("200"), (c) number of applications ("100"), (d) number of apps each consumer adds to demand set ("5"), (e) number of apps each platform offers ("5"), and (f) the ratio at which platform providers add and remove applications to/from their supply sets ("80/20"). We varied these parameters in a broad range (50%) and found that the changes in these parameters do not change the results qualitatively. Not surprisingly, the results change quantitatively due to the random parameters in the model, and the model completion times change based on the varying parameters. Therefore, we conclude that our results are robust (not sensitive to) the model parameters¹⁰. Next, we tested the model *structure*.

The experiments we conducted while we tested the model's sensitivity against the changes in the model *structure* revealed additional insights. As we conceptualized, complex adaptive platform markets are associated with a high level of unpredictability. Nonlinear interactions among the diverse agents in these markets lead to a kind of fundamental uncertainty that is not decomposable to parts (Arthur, 2013; Carley, 2005 in Baum, 2005). In this type of a market, the assumptions about the agents' access to information and their decision making structures could be critical. Agents in our model were assumed boundedly rational. That is, we assumed that consumers are not rational utility maximizers and platforms did not have perfect information. To test the effects of these assumptions on the results, we first relaxed the bounded rationality assumption for consumers, and tested the effect of breaching again. Table 1 (Experiment E) shows the results. In the setting where consumers are rational utility maximizers with perfect information about their choices and unlimited cognitive ability to evaluate these choices, the positive effects of breaching actions persist with a marginal significance (p -value is 0.0601 vis-à-vis 0.0106 in Experiment D). In this setting, breaching platforms perform better than their rivals 55.4% of the time (vis-à-vis 57.4% in Experiment D).

We also assumed that platform providers do not have perfect information about the fitness contributions of individual application offerings. In our original model, multi-sided platforms rely on the portion of the demand data they can access to make application offering decisions; hence, these decisions are not necessarily translated into high fitness contributions. Next, we relaxed this assumption, keeping in place the bounded rationality assumption for the consumers. We allowed platform providers to have perfect information about the fitness contributions of individual applications. The results are shown in Table 1

¹⁰ Due to the limited space, we do not report the details of the sensitivity analyses on model *parameters*.

(Experiment F). When a platform has the information on the fitness contributions of individual applications but consumers remain as being boundedly rational, breaching strategy has a negative effect on fitness ($p < 0.01$). In this setting, breaching platforms perform better than their rivals only 39.8% of the time. This is an interesting finding because platforms could be expected to improve their decisions with more information, and the improvement would be reflected in their fitness levels. To make sense of the results from these experiments, we ran another experiment where both consumers are rational utility maximizers and platforms have the perfect information. In a way, we defined both agent types according to rational choice theory. Table 1 (Experiment G) shows the results. Breaching strategy has a positive effect that is statistically significant ($p < 0.01$). Breaching platforms perform better than their rivals 59.0% of the time.

Our interpretation is as follows. In a turbulent, unpredictable market, not only the strategy to be pursued but also how it is pursued is important. First, when consumers are rational actors but platforms behave as if the demand sets of the consumers are not reliable and engage in experimentation instead, in an environment of perfect information, the contribution of breaching strategy is positive but only marginally significant. Second, when consumers are boundedly rational but platforms behave as if the consumers are rational actors and rely on consumer demand for their offering decisions instead of experimenting, the effect of breaching strategy on platform performance is negative. This may be because prospective customers may or may not be able to articulate their needs and preferences in their demand sets (Von Hippel, 1994); however, platform providers assume that the demand sets of consumers reflect their future actions. In reality, what consumers seem to demand in a time period may not be what they choose to adopt in the next time period. If platform providers use the learning from breaching in a market where consumers are boundedly rational behaving as if the consumers are rational actors, they begin to make poor decisions. In Experiments E and F, there is not a fit between the decision rules that platforms follow in implementing their strategies and consumer decision structures. We conclude that our findings on the effects of breaching strategy are robust to critical changes in model structure. However, the finding that a breaching strategy makes a positive, significant contribution to fitness inasmuch as the way the strategy implemented has a fit with consumer decision structures is interesting and require further theoretical and empirical investigation.

Conclusion

Our results showed that complementarity-based innovation strategy and breaching strategy, as we identified and conceptualized, contribute to platform performance in multi-sided platform markets. More specifically, we found that breaching strategy complements and positively reinforces the effects of the complementarity-based innovation strategy; i.e., the learning through breaching is valuable to the extent that it is leveraged by engaging in complementarity-based innovations. Even though the importance of learning and exploration is hardly controversial, we showed how exploratory and experiential learning can be prosecuted in the platform strategy context, and how such a strategy can translate into higher performance levels in a complex fitness landscape. Because the complexity arising from the nonlinear interactions of the system constituents as well as the network and lock-in effects leads to a morphing landscape in which existing peaks collapse and new peaks emerge constantly, multi-sided platforms could pursue the joint use of innovation and breaching as a strategy to achieve and sustain higher fitness levels.

We also contribute to the theory of multi-sided platform markets by showing that platform-based competitors should not necessarily focus on migrating consumers from rivals, and while doing so, struggle with the rivals' barriers such as strong network and lock-in effects. A breaching strategy can help multi-sided platform competitors achieve higher performance levels without having to migrate consumers, particularly in combination with the complementarity-based innovation strategy. We contribute to the practice of multi-sided markets by showing that even if a platform provider cannot eliminate the need for managing complexity, breaching and innovation strategies can help tame the challenges arising from it. Platform providers could take breaching actions into rival turfs and leverage them by complementarities.

Limitations

Our study has limitations in that we only manipulated three competitive strategies and assumed all other factors equal in our simulations. In practice, there are also variations in other parameters such as in revenue models of platforms, types of consumers and complementors, heterogeneity of independent developers, and a potential set of single-homing and multi-homing behaviors by consumers. Now that we built an experimental platform, where such variations can also be manipulated and simulated, future research can extend this study and further advance our understanding of the competitive dynamics in platform markets.

References

- Adjust. (2014). Birth, life and death of an app: A look at the Apple App Store in July 2014. Retrieved September 8, 2015, from https://www.adjust.com/assets/downloads/AppStore_Report2014.pdf
- Adner, R., Chen, J., & Zhu, F. (2014). Platform Competition and Compatibility Decisions: The Case of Apple's iPad vs. Amazon's Kindle. *Working Paper*.
- Alchian, A. A. (1950). Uncertainty, Evolution, and Economic Theory. *Journal of Political Economy*, 58(3), 211.
- Anderson, E. G., Parker, G. G., & Tan, B. (2014). Platform performance investment in the presence of network externalities. *Information Systems Research*, 25(1), 152–172.
- Argote, L., & Miron-spektor, E. (2011). Organizational Learning: From Experience to Knowledge. *Organization Science*, 22(5), 1123–1137.
- Armstrong, M. (2006). Competition in two-sided markets. *The RAND Journal of Economics*.
- Arthur, W. B. (2013). Complexity Economics: A Different Framework for Economic Thought. *Santa Fe Institute Working Paper*, 04-012.
- Ashby, W. R. (1958). Requisite variety and its implications for the control of complex systems. *Cybernetica*, 1, 1–13.
- Baum, J. A. C. (2005). The Blackwell Companion to Organizations. In *Companion to Organizations*.
- Beer, S. (1979). *The heart of enterprise* (Vol. 2). John Wiley & Sons.
- Beer, S. (1981). *Brain of the firm: the managerial cybernetics of organization*. J. Wiley New York.
- Beinhocker, E. (1999). Robust adaptive strategies. *Sloan Management Review*.
- Bharadwaj, S. G., Varadarajan, P. R., & Fahy, J. (1993). Sustainable Competitive Advantage in Service Industries: A Conceptual Model and Research Propositions. *Journal of Marketing*, 57, 83.
- Blattberg, R. C., & Deighton, J. (1996). Manage marketing by the customer equity test. *Harvard Business Review*, 74, 136–144.
- Boisot, M., & McKelvey, B. (2010). Integrating modernist and postmodernist perspectives on organizations: A complexity science bridge. *Academy of Management Review*, 35(3), 415–433.
- Boudreau, K. J. (2010). Open Platform Strategies and Innovation: Granting Access vs. Devolving Control. *Management Science*, 56(10), 1849–1872.
- Boudreau, K. J. (2012). Let a Thousand Flowers Bloom? An Early Look at Large Numbers of Software App Developers and Patterns of Innovation. *Organization Science*, 23(5), 1409–1427.
- Brooks, G. R. (1995). Defining market boundaries. *Strategic Management Journal*, 16, 535–549.
- Brown, S. L., & Eisenhardt, K. M. (1998). *Competing on the edge: Strategy as structured chaos*. Harvard Business Press.
- Burnham, T. a., Frels, J. K., & Mahajan, V. (2003). Consumer Switching Costs: A Typology, Antecedents, and Consequences. *Journal of the Academy of Marketing Science*, 31(2), 109–126.
- Caillaud, B., & Jullien, B. (2003). Chicken & egg: Competition among intermediation service providers. *RAND Journal of Economics*, 309–328.
- Cilliers, P. (1998). Complexity and postmodernism: understanding complex systems. Routledge.
- Cilliers, P. (2000). What Can We Learn From a Theory of Complexity? *Emergence*.
- Cilliers, P. (2001). Boundaries, hierarchies and networks in complex systems. *International Journal of Innovation Management*, 5(2), 135–147.
- Cohen, W. M., & Levinthal, D. a. (1994). Fortune favors the prepared firm. *Management Science*, 40(2), 227–251.
- Conway, R. (1959). Some problems of digital systems simulation. *Management Science*, 6(1), 92–110.
- Cyert, R. M., & March, J. G. (1963). *A behavioral theory of the firm*. Wiley-Blackwell. New York.
- D'Aveni, R. A. (1995). Coping with hypercompetition: Utilizing the new 7S's framework. *Academy of Management Perspectives*.
- D'Aveni, R. A., Dagnino, G. B., & Smith, K. G. (2010). The age of temporary advantage. *Strategic Management Journal*, 31, 1371–1385.
- D'Aveni, R. A., & Gunther, R. (1994). *Hypercompetition: Managing the Dynamics of Strategic Maneuvering*. Simon & Schuster Adult Publishing Group.
- Davis, J., Eisenhardt, K. M., & Bingham, C. B. (2007). Developing Theory Through Simulation Methods. *Academy of Management Review*, 32(2), 480–499.

- Eisenhardt, K. M. (1989). Making Fast Strategic Decisions in High-Velocity Environments. *Academy of Management Journal*, 32(3), 543–576.
- Eisenhardt, K. M., & Martin, J. a. (2000). Dynamic capabilities: what are they?, 21, 1105–1121.
- Eisenmann, T. R. (2007). Winner-take-all in networked markets. *Harvard Business School Note*.
- Eisenmann, T. R., Parker, G. G., & Alstyne, M. Van. (2006). Strategies for two-sided markets. *Harvard Business Review*.
- Eisenmann, T. R., Parker, G. G., & Van Alstyne, M. W. (2011). Platform envelopment. *Strategic Management Journal*, 32(12), 1270–1285.
- Evans, D. S. (2003). Some Empirical Aspects of Multi-sided Platform Industries. *Review of Network Economics*, 2(3), 191–209.
- Farrell, J., & Klemperer, P. (2007). Coordination and lock-in: Competition with switching costs and network effects. *Handbook of Industrial Organization*, 3(06).
- Fuentelsaz, L., Maicas, J., & Polo, Y. (2012). Switching costs, network effects, and competition in the European mobile telecommunications industry. *Information Systems Research*, 23(1), 93–108.
- Gandal, N. (1995). Competing Compatibility Standards and Network Externalities in the PC Software Market. *The Review of Economics and Statistics*, 77(4), 599–608.
- Gawer, A. (2009). Platform dynamics and strategies: from products to services. In *Platforms, Markets and Innovation* (pp. 45–76).
- Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W. M., Railsback, S. F., ... DeAngelis, D. L. (2005). Pattern-oriented modeling of agent-based complex systems: lessons from ecology. *Science (New York, N.Y.)*, 310, 987–991.
- Hagiu, A. (2006). Multi-sided platforms: From microfoundations to design and expansion strategies. *Harvard Business School Strategy Unit Working Paper*, 1–25.
- Hagiu, A. (2007). Merchant or Two-Sided Platform? *Review of Network Economics*, 6(2), 115–133.
- Hagiu, A., & Spulber, D. (2013). First-Party Content and Coordination in Two-Sided Markets. *Management Science*, 59(4), 933–949.
- Hagiu, A., & Wright, J. (2013). Marketplace or reseller? *Harvard Business School Note*.
- Holland, J. H. (1975). *Adaptation in Natural and Artificial Systems*. Ann Arbor MI University of Michigan Press.
- Holland, J. H. (1995). *Hidden order: How adaptation builds complexity*. Addison Wesley.
- Huber, G. P. (1991). Organizational Learning: The Contributing Processes and the Literatures. *Organization Science*, 2(1), 88–115.
- Katz, M. L., & Shapiro, C. (1985). Network Externalities, Competition, and Compatibility. *The American Economic Review*, 75(3), 424–440.
- Kaufmann, S. (1993). *The origins of order*. Oxford University Press (Vol. 209).
- Lampel, J., Shamsie, J., & Shapira, Z. (2009). Experiencing the Improbable: Rare Events and Organizational Learning. *Organization Science*, 20(5), 835–845.
- Lampel, J., & Shapira, Z. (2001). Judgmental Errors, Interactive Norms, and the Difficulty of Detecting Strategic Surprises. *Organization Science*, 12(5), 599–611.
- Lant, T., Milliken, F., & Batra, B. (1992). The role of managerial learning and interpretation in strategic persistence and reorientation: An empirical exploration. *Strategic Management Journal*, 13(8), 585–608.
- Lee, C.-H., Venkatraman, N., Tanriverdi, H., & Iyer, B. (2010). Complementarity-based hypercompetition in the software industry: Theory and empirical test, 1990–2002. *Strategic Management Journal*, 31(13), 1431–1456.
- Lemelin, A. (1982). Relatedness in the patterns of interindustry diversification. *The Review of Economics and Statistics*.
- Levinthal, D. A. (1997). Adaptation on Rugged Landscapes. *Management Science*, 43(7), 934–950.
- Levinthal, D. A., & Siggelkow, N. (2001). Linking the old and the new: modular and integrated adaptation to the internet. In *The Academy of Management Meeting*. Washington, DC.
- Levinthal, D. A., & Warglien, M. (1999). Landscape design: Designing for local action in complex worlds. *Organization Science*, 10(3).
- Levitt, B., & March, J. G. (1988). Organizational Learning. *Annual Review of Sociology*, 14(1), 319–338.
- Maguire, S., & McKelvey, B. (2006). Complexity Science and Organization Studies. *The SAGE Handbook of Organization Studies*.
- March, J. G. (1991). Exploration and Exploitation in Organizational Learning. *Organization Science*, 2(1).
- March, J. G., & Simon, H. A. (1958). Organizations. In *Organizations* (pp. 34–111).

- March, J. G., Sproull, L., & Tamuz, M. (1991). Learning from samples of one or fewer. *Organization Science*.
- McDaniel, R. R., Jordan, M. E., & Fleeman, B. F. (2003). Surprise, Surprise, Surprise! A complexity science view of the unexpected. *Health Care Management Review*, 28(3), 266–78.
- McGrath, R. (2001). Exploratory learning, innovative capacity and management oversight. *Academy of Management Journal*, 44(1), 118–131.
- McKelvey, B. (2001). Energising order-creating networks of distributed intelligence: improving the corporate brain. *International Journal of Innovation Management*.
- Miller, C. C., Ogilvie, D., & Glick, W. H. (2006). Assessing the External Environment: An Enrichment of the Archival Tradition. *Research Methodology in Strategy and Management*, 3(06), 97–122.
- Nelson, R. R., & Winter, S. G. (1977). Simulation of Schumpeterian Competition. *American Economic Review*, 67(1), 271–276.
- Nelson, R. R., & Winter, S. G. (1982). *An evolutionary theory of economic change*. Cambridge MA Belknap (Vol. 93).
- Page, S. E. (2009). *Understanding complexity*. Teaching Company Chantilly, VA.
- Parker, G. G., & Alstyne, M. Van. (2005). Two-sided network effects: A theory of information product design. *Management Science*, 51(10), 1494–1504.
- Pisano, G. P. (1994). Knowledge, integration, and the locus of learning: An empirical analysis of process development. *Strategic Management Journal*, 15(S1), 85–100.
- Railsback, S. F., & Grimm, V. (2011). *Agent-based and individual-based modeling: a practical introduction*. Princeton university press.
- Ram, S., & Jung, H. (1990). The conceptualization and measurement of product usage. *Journal of the Academy of Marketing Science*.
- Repenning, N. (2002). A simulation-based approach to understanding the dynamics of innovation implementation. *Organization Science*, 13(2), 109–127.
- Rivkin, J. W. (2000). Imitation of Complex Strategies. *Management Science*, 46(6), 824–844.
- Rivkin, J. W., & Siggelkow, N. (2002). Organizational sticking points on NK Landscapes. *Complexity*, 7(5), 31–43.
- Rochet, J., & Tirole, J. (2003). Platform competition in two-sided markets. *Journal of the European Economic Association*.
- Rochet, J., & Tirole, J. (2006). Two-sided markets: a progress report. *The RAND Journal of Economics*, 37(3), 645–667.
- Romme, A. G. L. (2004). Unanimity Rule and Organizational Decision Making: A Simulation Model. *Organization Science*, 15(6), 704–718.
- Sargut, G., & McGrath, R. G. (2011). Learning to live with complexity. *Harvard Business Review*, 89(9), 68–76, 136.
- Schumpeter, J. (1942). *Socialism, capitalism and democracy*. Routledge.
- Shankar, V., & Bayus, B. L. (2003). Network effects and competition: an empirical analysis of the home video game industry. *Strategic Management Journal*, 24(4), 375–384.
- Sheremata, W. A. (2004). Competing through innovation in network markets: Strategies for challengers. *Academy of Management Review*, 29(3), 359–377.
- Siggelkow, N. (2001). Change in the presence of fit: The rise, the fall, and the renaissance of Liz Claiborne. *Academy of Management Journal*, 44(4), 838–857.
- Simon, H. A. (1955). A Behavioral Model of Rational Choice. *The Quarterly Journal of Economics*, 69(1), 99–118.
- Simon, H. A. (1962). The architecture of complexity. *Proceedings of the American Philosophical Society*, 106(6), 467–482.
- Simon, H. A. (1979). Rational decision making in business organizations. *The American Economic Review*, 69(4), 493–513.
- Simon, H. A. (1991). Bounded Rationality and Organizational Learning. *Organization Science*, 2(1), 125–134.
- StatCounter. (2014). StatCounter Global Stats: Top 9 Browsers from Dec 2008 to Dec 2014. Retrieved September 8, 2015, from <http://gs.statcounter.com/#all-browser-ww-monthly-200812-201412>
- Statista. (2013). Groupon's daily deal market share in the United States in 2013. Retrieved September 8, 2015, from <http://www.statista.com/statistics/322293/groupon-market-share-us/>
- Statista. (2014). Mobile operating system U.S. market - Statista Dossier. Retrieved September 8, 2015, from <http://www.statista.com/study/11519/mobile-operating-system-us-market-statista-dossier/>

- Statista. (2015). Global unit sales of current generation video game consoles from 2008 to 2014. Retrieved September 8, 2015, from <http://www.statista.com/statistics/276768/global-unit-sales-of-video-game-consoles/>
- Sterman, J. D. (2006). Learning from evidence in a complex world. *American Journal of Public Health*, 96(3), 505–14.
- Tanriverdi, H., & Lee, C.-H. (2008). Within-Industry Diversification and Firm Performance in the Presence of Network Externalities: Evidence From the Software Industry. *Academy of Management Journal*.
- Tanriverdi, H., Rai, A., & Venkatraman, N. (2010). Research Commentary —Reframing the Dominant Quests of Information Systems Strategy Research for Complex Adaptive Business Systems. *Information Systems Research*, 21(4), 822–834.
- Tanriverdi, H., & Venkatraman, N. (2005). Knowledge relatedness and the performance of multibusiness firms. *Strategic Management Journal*, 26(2), 97–119.
- Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management, 18(7), 509–533.
- Topkis, D. M. (1998). *Supermodularity and complementarity*. Princeton University Press.
- Vasile, C. (2014). BlackBerry Confirms BBM Will Not Come to Windows Phone Anytime Soon. 2014. Retrieved May 3, 2014, from <http://news.softpedia.com/news/BlackBerry-Confirms-BBM-Will-Not-Come-to-Windows-Phone-Anytime-Soon-418259.shtml>
- Venkatraman, N., & Lee, C. (2004). Preferential linkage and network evolution: A conceptual model and empirical test in the US video game sector. *Academy of Management Journal*, 47(6), 876–892.
- Viard, V. B. (2007). Do switching costs make markets more or less competitive? The case of 800-number portability. *RAND Journal of Economics*, 38, 146–163.
- Von Hippel, E. (1994). “Sticky Information” and the Locus of Problem Solving: Implications for Innovation. *Management Science*, 40(4), 429–439.
- West, J. (2003). How open is open enough? Melding proprietary and open source platform strategies. *Research Policy*, 32(7), 1259–1285.
- Whittaker, Z. (2012). Google has “no plans” to build apps for Windows 8, Windows Phone 8 | ZDNet. 2012. Retrieved May 3, 2014, from <http://www.zdnet.com/google-has-no-plans-to-build-apps-for-windows-8-windows-phone-8-7000008736/>
- Wholey, D. R., & Brittain, J. (1989). Characterizing Environmental Variation. *Academy of Management Journal*.
- Wiggins, R. R., & Ruefli, T. W. (2005). Schumpeter’s ghost: Is hypercompetition making the best of times shorter? *Strategic Management Journal*, 26, 887–911.
- Wright, S. (1931). Evolution in Mendelian populations. *Genetics*, 16(2), 97.
- Wright, S. (1932). The roles of mutation, inbreeding, crossbreeding, and selection in evolution. In *Proceedings of the Sixth International Congress of Genetics*. Ithaca, New York.
- Yoffie, D. B., & Rossano, P. (2012). Apple Inc. in 2012. *Harvard Business School Case*.
- Zhu, F., & Iansiti, M. (2007). Dynamics of platform competition: Exploring the role of installed base, platform quality and consumer expectations. *Working Paper*.
- Zhu, F., & Iansiti, M. (2012). Entry into platform based markets. *Strategic Management Journal*, 33, 88–106.
- Zott, C. (2003). Dynamic capabilities and the emergence of intraindustry differential firm performance: insights from a simulation study. *Strategic Management Journal*, 24(2), 97–125.

Appendix A: The Execution Steps of the Simulation Model

Before the Steps (Initialization)

1. 100 apps are created and pairwise complementarity scores are randomly assigned to these apps.
2. Consumers/platforms add 5 random complementary apps to their demand/supply sets.
3. Consumers select and adopt the platform that provides the highest utility.

At Each Step (Time Periods)

1. Pairwise complementarity scores are updated based on the consumers' selections.
2. A randomly selected number of consumers reevaluate alternative the platforms and choose a platform to adopt (if not adopted before), or choose a platform to switch to:
 - a. If only one platform provides the highest utility¹¹ and a consumer satisfies the switching cost criterion, then the consumer selects the platform.
 - b. If more than one platform provides the same amount of utility to a consumer and the consumer satisfies the switching cost criterion, then the consumer selects randomly.
 - c. If there is not a platform that provides a higher amount of utility than the current utility a consumer has, then the consumer does not make a selection.
3. Consumers' utility scores and the number of consumers platforms have are updated.
4. Platforms' fitness levels are updated and consumers' tenures on a platform are updated.
5. Three application lists are created for each platform:
 - a. A list of the applications that are demanded by own consumers,
 - b. a list of the applications that are demanded but currently not offered,
 - c. and a list of the applications that are demanded and currently offered.
6. Consumers add/remove a new app:
 - a. 80% of the time, consumers add a new random app to their demand sets.
 - b. 20% of the time, consumers remove the app that provides the lowest utility.
7. Platforms add/remove a new app:
 - a. 80% of the time, platforms add a new app to their supply sets in two ways:
 - i. 90% of the time, they add an app that is demanded by their consumers and already offered by the other platforms in the landscape (imitation). They choose the app that is demanded the most¹². If there are multiple, they choose randomly.
 - ii. 10% of the time, they add an app that is demanded by their consumers the most¹¹. If there are multiple, they choose randomly.
 - b. 20% of the time, they remove the app that is demanded the least and that contributes to fitness the least. If there are multiple, they choose randomly.
8. Innovation: If a platform is manipulated for innovation, it adds a new app that is demanded by their consumers and not yet offered by the other platforms in the landscape under performance constraints. The platform chooses the app that is demanded the most¹³. If there are multiple, it chooses randomly.
9. Breaching: If a platform is manipulated for breaching, it lists the applications in its supply set, identifies those that are not offered by its rivals with the highest number of consumers, and offer the app that is demanded the most¹³ to the rival platform with the highest number of consumers. If there are multiple, they choose randomly.

¹¹ Consumers are assumed boundedly rational and they make mistakes in comparing potential utilities.

¹² The most demanded app is *not* necessarily the app that provides a significant fitness contribution.

¹³ Innovations/breaching can (and do) fail in the model because the most demanded application is not necessarily the one that makes a significant enough contribution to platform fitness.