Winner does not take all: Selective attention and local bias in platform-based markets

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ABSTRACT

We model how macro-level dynamics of platform competition emerge from micro-level interactions among consumers. We problematize the prevailing winner-take-all hypothesis and argue that instead of assuming that consumers value the general connectivity of an entire network, they are selectively attentive and locally biased. We contrast several alternative agent-based models with differing sets of assumptions regarding consumer agents' behavior and compare their predictions with empirical data from the competition between Sony's PlayStation 3 and Microsoft's Xbox 360. The results show that only when consumers are assumed to be selectively attentive and locally biased is it possible to explain real-life market sharing between the given platforms. In effect, it is shown how a late-entrant platform can get adopted by most consumers in the market, despite the fact that an early entrant has greater initial installed base, greater pool of complementary products, and lower initial price.

Keywords: Adoption behavior; agent-based modeling; complementarities; network effects; platform competition; simulation

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1 INTRODUCTION

Organizational fields are increasingly organized as platform ecosystems, where the platform refers to "a set of shared core technologies and technology standards [that] supports value co-creation through specialization and complementary offerings" (Thomas, Autio, & Gann, 2014, p. 201). Apart from the provision of a shared core, the platform mediates interactions among different users, such as consumers and providers of complementary products. In addition, platforms and their ecosystems compete against each other in platform-based markets. Previous literature on platform competition has explained the competitive outcomes in platform-based markets from a variety of perspectives. Grounded in the literature on industrial economics and two-sided markets (Evans & Schmalensee, 2007), both global and local network effects have been noted to have an impact on the market penetration of platforms. Building upon the notion of network effects, strategic management literature has focused mainly on the strategies platform owners can utilize to leverage network effects to their advantage (Cennamo & Santalo, 2013; Lee, Lee & Lee, 2006). In addition to these factors, the decisions of users of the platform, both the providers of complementary products as well as consumers, have been under scrutiny. For example Kang and Downing (2015) explored supplier networks' impact on competition between WiMAX and 3G/LTE whereas Venkatraman and Lee (2004) studied the product launch decisions of complementary game providers, and Zhu and Iansiti (2012) examined the expectations of the consumers (i.e., the players) in the same video game console market.

Platform-based markets as two-sided markets are characterized by indirect network effects (Katz & Shapiro, 1986), where the demand for the platform on one side of the market will subsequently affect the demand for the platform on the other side of the market (Clements & Ohashi, 2005; Rochet & Tirole, 2006). Thus, a platform with greatest pool of complementary products should attract most of the new end users which then stimulates further support by complementors, eventually resulting in self-reinforcing demand dynamics. This logic suggests that tipping—all players and video game developers select the same platform—is an equilibrium in these markets (Hossain et al., 2011). Hence, two-sided markets, including platform-based markets such as the video game console markets, are often called winner-take-all markets (see e.g., Schilling, 2002; Eisenmann et al., 2006; Lee et al., 2006).

Due to the prevalence of network effects, literature suggests (conditionally) that a platform provider should expand its installed base of users rapidly in order to attract more complementary product providers to the platform. Such a get-big-fast strategy is likely to result in self-reinforcing loop and hence, in winner-take-all outcome (i.e., one platform takes over the entire market) even with inferior quality to competing platforms (Lee, Lee & Lee 2006; McIntyre & Subramaniam, 2009; Zhu & Iansiti, 2012; Cennamo &

Santalo, 2013). In other words, it would be expected that an early entrant[1] platform with a greater initial installed base, greater pool of complementary products and lower initial price would be adopted by most adopters. Yet, we have an exciting empirical example on the competition between two video game consoles, namely PlayStation 3 and Xbox 360, where the most consumers adopted the late entrant (i.e., PlayStation 3) despite the fact that Xbox 360 had all the aforementioned potential advantages. In this study, we aim to explain this "winner does not take all" market outcome since we believe that such an attempt can open up new important insights on the dynamics of competition in platform-based markets.

In this study, we challenge the assumption on the causality between the size of the installed base and winner-take-all outcome. First, we incorporate a field-level assumption of selective attention (Assumption 1) into our study. Consumers are not perfectly rational utility maximizers and, as research on consumer behavior and psychology in general has consistently shown, consumers have limited attentional capability when making decisions (Kahneman, 1973). We acknowledge that the assumption that humans are selectively attentive is a widely accepted one; however, to the best of our knowledge, our study is the first to incorporate demand-side dynamics at the micro-level and take into account the selective attention of consumers in the research on platform-based markets. Specifically, we assume that the consumers' attention toward complementary products and thus their perceived qualities are affected by the introduction of new complementary product quality to the market, which then affects the utility of platforms and hence their adoption. In the spirit of problematization (Alvesson & Sandberg, 2011), we challenge a domain specific assumption, namely the assumption related to the size of the installed base and introduce a field-level assumption of selective attention to this domain.

In addition, extending the work of Lee, Lee, and Lee (2006) and Afuah (2013), we develop an alternative assumption ground for the theory on platform competition by stating that consumers derive utility from their local network, that is, from other consumers who interact with them. Recently, the assumptions underlying the current literature on platform competition have been criticized for the overly simplistic view on network effects, behavior of the consumers, and the overemphasis of the size of the installed base (Afuah, 2013; Lee, Lee, & Lee, 2006). The global network effects—that is, the size of the network—is not all that matters and the value of network effects is more likely to arise from a specific structure of the network and its behavior (Afuah, 2013). Social networks influence individuals (Goel & Goldstein, 2013). In particular peer-effect can lead to local bias (Assumption 2), a situation where acquaintances in the same social network adopt a lagging technology with a smaller installed base than the leading technology (Lee, Lee, & Lee, 2006).

[1] As Xbox 360 was the first 7th generation video game console launched, we will refer to it as early entrant. The later launched PlayStation 3 will be referred to as late entrant.

We contrast several alternative agent-based models with differing sets of theoretical assumptions regarding consumer agents' behavior and compare their predictions with empirical data from the competition between Sony's PlayStation 3 and Microsoft's Xbox 360. Our results show that the developed assumptions (i.e., selective attention and local bias) are crucial to explaining why PlayStation 3 eventually obtained most adopters, and that the other sets of theoretical assumptions cannot explain the market outcome. In effect, we show that the competitive advantage that a late-entrant has in terms of complementarities (i.e., the perceived quality of complementary products) can compensate for its disadvantage in terms of local direct network effects, thereby allowing it to penetrate the market and be adopted by most consumers.

Our study offers the following contributions. We contribute to the theory of competition in platform-based markets by introducing a field-level assumption of selective attention to this domain. Further, we extend the work of Lee, Lee, and Lee (2006) and Afuah (2013) by empirically showing that consumers derive value from their local network, that is, that they are locally biased. Only recently, the specific structure of the network where network effects arise has been listed as an important avenue for future research (Lee, Lee & Lee, 2006; Rahmandad & Sterman, 2008; Afuah, 2013). With empirical data, we test different sets of theoretical assumptions and show that the market outcomes are not counterintuitive when we examine the competition in light of the developed assumptions. All in all, by focusing on demand-side dynamics we show that the division of the market between platforms is shaped by the sequential decisions of the adopters, who are selectively attentive and influenced by the local bias in their social network. Finally, we claim that while relying on established procedures, the applied approach is a practically useful example on empirical validation of agent-based simulation models that continues to be a nontrivial task (Windrum, Fagialo & Moneta, 2007; Rand & Rust, 2011).

2 THEORETICAL BACKGROUND

2.1 Competition in Platform-based Markets

A multitude of industries are organized around platforms that provide a technological core to connect and facilitate transactions among several parties (Eisenmann, Parker, & Van Alstyne, 2006; Zhu & Iansiti, 2012). Such settings are called platform-based markets (Eisenmann, Parker, & Van Alstyne, 2006; Zhu & Iansiti, 2012), and the structure of the platform-based market is two or multi-sided when an intermediary (i.e., platform) must succeed in bringing both sides of the market (i.e., customers and suppliers) together. Numerous examples exist, including credit cards, which bring together credit card holders and merchants; shopping malls that bring together buyers and sellers; PC operating systems that bring together software providers and customers; and smartphones that bring together application providers and customers (for more illustrative examples, see Evans, 2003; Rochet & Tirole, 2003; Eisenmann, Parker & Van Alstyne, 2006; Afuah, 2013). Another example is the video game console market, where platform providers, such as Sony and Microsoft each produce game consoles, are associated with their own developer and player communities (for a more detailed description of the video game console market, see Daim, Justice, Hogaboam, Mäkinen & Dedehayir, 2014).

Platforms offer little value to the end-user without complementary products. For example, the usefulness of a computer to a consumer depends largely on the complementarities, the software. Thus, the quality of the platform is partially dependent on the quality of the complementary products. In platform-based markets, consumers adopt the platform and in addition the complementary products; in the video game console markets consumer adopt both video game consoles and video games. The relationship between the platform and complementary products is a complex one as different actors typically provide the hardware and software. Traditionally, the adoption in markets with indirect network effects has been modeled with contingent diffusion models where complementary products create demand contingencies (Gupta, Jain, & Sawhney, 1999). In essence, consumers derive value from the availability of complementary goods (indirect network effects) (Schilling, 2003; McIntyre & Subramaniam, 2009).

Competition between platforms in platform-based markets has been explained with a multitude of factors. First, there exist explanations that explicate performance outcomes (e.g., market penetration) with platform-exogenous characteristics such as network effects (McIntyre & Subramaniam, 2009). When one user joins and expands the network, the value of membership to another user increases (Arthur, 1989; Katz & Shapiro, 1986). Thus, network effects are typically portrayed as a function of the installed base, cumulative number of consumers at any given time, and marginal impact of a unit increase in network size of demand—the network strength (McIntyre & Subramaniam, 2009). These direct network effects can be either global or local. When global direct network effects are present, all agents are connected, communication is easy, and diffusion can progress (Arthur, 1989).

Second, competitive outcomes between platforms have been explained with platform-related characteristics, such as platform quality (Zhu & Iansiti, 2012) and technological functionality (Daim, Justice, Hogaboam, Mäkinen & Dedehayir, 2014; Schilling, 2003), and differences in strategies (McIntyre & Subramaniam, 2009). As network effects are strategic resources to platforms (Shankar & Bayus, 2003), platforms deploy strategic initiatives to leverage network effects to create competitive advantage (McIntyre & Subramaniam, 2009). These initiatives include, for example, get-big-fast strategies (Cennamo & Santalo, 2013), consumer expectation management, firm diversification, and decisions related to entry timing (McIntyre & Subramaniam, 2009). The typical argument for order-of-entry effect in platform-based markets is that a platform, which has a small lead on both sides of the market, can attract more consumers and more complementors and, thus, take over the entire market even with inferior quality (McIntyre &

Subramaniam, 2009; Zhu & Iansiti, 2012). Given the possibility of the winner-take-all (WTA) outcome—a hypothesis that states the outcome of competition between incompatible technologies (Lee, Lee, & Lee, 2006)—Cennamo and Santalo (2013), for example, emphasize that "platform firms should embrace aggressive strategies to expand both their installed based on users and their stable of application providers so that the benefits achieved on each side are mutually reinforcing" (p. 1332). The strategy, get-big-fast, highlights the importance of rapidly acquiring and growing a platform's installed base of users, locking-in those users and undermining the ability of rival platforms to do the same (Lee, Lee, & Lee, 2006). This strategy assumes that consumers value the general connectivity of an entire network (Afuah, 2013), thereby leading to the formulation of the WTA hypothesis (Lee, Lee, & Lee, 2006).

2.2 Assumption 1: Selective attention—Limited Attentional Capability and Utility Maximization

When making decisions to adopt, consumers need to process adoption-related information to make a choice. Cognition refers to information processing and attention, as a cognitive process refers to a process by which an individual concentrates mental activity on a stimulus (Bagozzi, Gürhan-Canli, & Priester, 2002). Attention is a mental resource that is essential in information processing, exists in a limited amount, and can be allocated flexibly to various sources of information (Lavie & Fox, 2000). Attention is always selective and humans have limited attentional capability (Kahneman, 1973; Ocasio, 1997); people attend only to certain stimuli, and individuals are more likely to attend to a stimulus if the stimulus is personally relevant, unexpected, interesting, and salient (Bagozzi, Gürhan-Canli & Priester, 2002). For example, in contrast to redundant information, novel information is attention-drawing (Kahneman 1973). The limited-capacity model of attention (Kahneman, 1973) states that the limited attentional capability of humans results in their bounded capability to be rational (Ocasio, 1997), a widely researched human characteristic both in the literature of managerial decision-making (Simon, 1947) and consumer behavior research (Lee & Faber, 2007).

To illustrate the relevance of limited attentional capability in platform-based markets, Zhu and Iansiti (2012) note that consumers typically have favorable expectations from established platforms, as they believe that everyone else will adopt the same platform. Further, people wait for others to adopt a platform before making the decision to adopt it (Srinivasan, Lilien, & Rangaswamy, 2004). In their adoption decisions, consumers attempt to make a choice that will benefit them as much as possible. However, as discussed by Kahneman and Thaler (2006), in utility maximization, the one making the adoption decision must begin by making forecasts regarding the various possible outcomes. Further, if there is a bias in the forecast, "then choices will systematically fail to maximize utility" (Kahneman & Thaler, 2006: 231). Thus, limited attentional capability, selective attention, and bounded rationality are also at play in how consumers judge benefits and utility, and they are among a variety of reasons due to which forecasts of future utility tend to be biased. In this paper, we assume that the novelty of complementary products is a factor mattering for platform competitiveness along with the quality of the complementary products. Specifically, we assume that the consumers pay relatively more attention to newer complementary products, and thus perceive them relatively better (as opposed to older complementary products in the market), when the availability of high quality products in the market increases. This selectively attentive behavior then affects the utility of platforms and hence their adoption.

2.3 Assumption 2: Local Bias—Local Direct Network Effects and Network Structure

Network effects are interactions within a population of heterogeneous agents facing a technological choice (Dalle, 1997). In certain contexts, the patterns of interactions are very specific, giving rise to local network effects. Thus, consumers do not benefit from general connectivity to an entire network; they benefit from connectivity to acquaintances, that is, local network effects. As illustrated with an example by Banerji and Dutta (2009), the utility of a piece of software for a researcher is partially dependent "on the number of her research collaborators who use the same package, rather than the total number of users of the package" (p. 605). People may think globally, but in general, they act locally (Tomochi, Murata, & Kono, 2005) and are influenced by the opinions and choices of their acquaintances instead of the entire installed base (Lee, Lee, & Lee, 2006). Several studies have shown that replacing the assumption of global network effects with the assumption of local network effects will lead to more realistic explanations of how consumers adopt new products in markets with network effects (Tomochi, Murata, & Kono, 2005) and the competitive outcomes in markets with network effects (Lee, Lee, & Lee, 2006; Banerji & Dutta, 2009).

Local direct network effects have been argued to generate value for the consumer from the perspective of the social network structure (cf. Afuah, 2013). Previous research has identified random, small-world, and regular networks (Watts & Strogatz, 1998) and also scale-free networks (Barabási & Albert, 1999). Random and regular networks are two opposites: random networks exhibit poor clustering whereas regular networks are highly clustered networks (Watts & Strogatz, 1998), where any pair of individuals are likely to share acquaintances, as easily seen in friends and family networks (Choi, Kim, & Lee, 2010). Small-worlds resemble regular networks with varying amounts of disorder; they can be highly clustered, yet with short characteristic path length (Watt & Strogatz, 1998), and real social networks often exhibit these small-world characteristics. Milgram (1967) was the first to discover evidence for the existence of short pathways that keep the diameter of the global social network small. Newman (2001) uses data on scientific literature co-authorship to show that researcher networks are clustered and connected through short pathways. The first world-scale computational experiment on Facebook data shows four degrees of separation (Backstrom et al., 2012).

However, previous research on how the complex structure of a social network affects the realization of local direct network effects is very scant. Among the few, Lee, Lee, and Lee (2006) utilized the algorithm given by Watts and Strogatz (1998) and applied a span of possible topologies between a regular network and a random network in their study of how local network effects that lead to local bias (i.e., a situation where acquaintances in the same social network adopt a lagging technology with a smaller installed base than the leading technology) might impede WTA outcomes. Specifically, Lee, Lee and Lee (2006) found that the WTA outcome is more unlikely the more clustered the consumer network is, despite the diameter of the network remains small (Watts and Strogatz, 1998). We also employ Watts and Strogatz (1998) model of small-world network to test whether we can replicate the finding of Lee, Lee and Lee (2006) that a highly clustered small-world network tends to preserve local bias and impedes the WTA outcome.

3 METHODOLOGY

3.1 Approach and shared architecture for alternative models

We focus on modeling the adoption of competing platforms by consumers. We model consumers' selection of a platform (which platform to adopt), while their adopting time decisions (when to adopt a platform) are determined by the data. We restrict ourselves to explaining consumer adoption only, thereby implying that all the decisions of platform providers and complementary product providers are determined by the data. We construct four alternative models with four alternative sets of theoretical assumptions about how consumers select a platform that all share common model architecture, and we compare their predictive accuracy in an empirical setting[2].

The alternative models to be presented are all implemented as agent-based simulation models. Agent-based modeling is a form of computational simulation that enables the construction of systems on an agent-

[2] It is obvious that we cannot test for all assumptions in one paper. We restrict ourselves to challenging the assumptions presented in the theoretical section. Nevertheless, the following assumptions are also be made and are common to all alternative models in this paper. First, we assume that consumers consider all platforms as viable options when adopting a platform. As long as this assumption holds, it is possible to explain the selection of a platform and adoption time decision separately. Regarding our empirical setting, PlayStation 3 and Xbox 360 were arguably targeted to the same audience and we see no obvious reason for the platform adoption decisions being predetermined, especially due to that the games published on the previous generations of the two consoles were mostly unplayable on PlayStation 3 (Sony, 2015) and Xbox 360 (Microsoft, 2015), a factor that might explain brand loyalty. Second, we assume that each consumer adopts a platform only once and adopts only one platform. Obviously, this assumption is not applicable to all platform-based markets, but it is justifiable when it is relatively uncommon to adopt multiple platforms or repurchase. Indeed, this assumption is typically made when studying video game console markets (e.g., Clements & Ohashi, 2005; Corts & Lederman, 2009; Zhu & Iansiti, 2012), because it is reportedly uncommon to adopt multiple video game consoles: for example both Corts and Lederman (2009) and Zhu and Iansiti (2012) refer to the data from the NPD group, showing that, for both the sixth (PlayStation 2 and Xbox) and seventh (PlayStation 3 and Xbox 360) generations of consoles, 5% or less of U.S. consumers/households owned multiple consoles belonging to the same console generation. Further, we have made some assumptions about the empirical data that will be discussed later in the methodology section.

level (an agent is a meaningful decision-making unit that may represent a consumer, company, piece of equipment, etc.), and simulating both the micro-level behavior of multiple agents and the macro-level behavior of the entire system arising from agent-level interactions over time (Macal & North, 2010; Macy & Willer, 2002). Agent-based modeling is a useful method for research, particularly in terms of theory development (Davis, Eisenhardt, & Bingham, 2007; Harrison, Jin, Carroll, & Carley, 2007) as it can reveal the complex theoretical relationships among constructs or the outcomes of interactions among various organizational and strategic processes (Davis, Eisenhardt, & Bingham, 2009). In addition, simulation can help to understand phenomena as they unfold over time (Repenning, 2002). In this paper, agent-based modeling is used, since constructing a dynamic model that involves consumer interactions and incorporates local direct network effects is impossible unless a consumer (i.e., an agent) level is considered, which is possible with agent-based modeling.

Beyond pure theoretical modeling, we aim for testing the validity of the alternative models empirically through comparing their output directly to the real world observations. This means that we compare the predictive accuracy of the alternative models in order to determine the most valid model. Like with any simulation model, showing that the output of an agent-based model closely resembles empirical data is the key test of validity (Law & Kelton, 2000; Rand & Rust, 2011). One of the virtues of agent-based modeling is that is enables exploring the validity of model assumptions that is not either possible or even desirable with other modeling and simulation methods (e.g., neoclassical economists restrict exploring the underlying assumptions of their models). However, empirical validation is not a trivial task with agent-based models (Windrum, Fagialo & Moneta, 2007) and only recently there has been growing interest in empirical validation and prediction among agent-based modelers (see for example, Palmer, Sorda & Madlener, 2015; Schwartz & Ernst, 2009; Shafiei, Thorkelsson, Ásgeirsson, Davidsdottir, Raberto & Stefansson, 2012; Wolf, Schröder, Neumann, & Haan, 2015). Paradoxically, one of the main problems in predicting with agent-based models is the fact that they are often too descriptive. Too detailed of a model can generate “any result” (Windrum, Fagialo & Moneta, 2007, p. 13) or “fit any data” (Rand & Rust, 2011, p. 182) but too simplistic of a model cannot cope with the complexity of the real world (Shin & Park, 2009). In this paper, through using real world data as input to the alternative models, we control for the behavior of other than the consumer agents (i.e., platform and complementary product providers) that significantly reduces model complexity and output variance as only consumer adoption must be modeled. Further, we embrace simplicity by fixing the shared model architecture and by using only few exogenous parameters in an alternative model at most. Following these approaches, we believe that if an alternative model were able to replicate the observed market dynamics, it would be highly unlikely it does so by chance and thus the model would be valid.

To explain the shared model architecture, the market consists of n_{it} consumers, n_{jt} platforms, and n_{kt} complementary products for the platforms at time t ($t = 1,2,\ldots,n_t$), i.e., the agents enter and act in the market over time. The overall value of a platform P_j for a consumer E_i at time t comprises of n_v value indicators V_{ijtv}. Dividing a value indicator by the price $p_{jt} > 0$ of the platform (i.e., the price of adoption for a consumer) at time t yields a utility indicator U_{ijtv}. One could think of a utility indicator as how much specific type of "value for the money" a consumer receives from adoption. A corresponding utility index $I_{U_{ijtv}}$ describes how much specific type of utility the platform provides for a consumer relative to competing platforms at time t. To clarify, for a consumer the utility index of a platform P_x ($x \in j$) at time t is calculated in the following manner:

$$I_{U_{ixtv}} = \frac{\frac{V_{ixtv}}{p_{xt}}}{\frac{\sum_{j=1}^{n_{jt}} \frac{V_{ijtv}}{p_{jt}}}{n_{jt}}} = \frac{U_{ixtv}}{\frac{\sum_{j=1}^{n_{jt}} U_{ijtv}}{n_{jt}}} \ . \tag{1.}$$

A consumer chooses to adopt the platform that has the largest overall utility index $I_{U_{ijt}}$; that is, the platform that offers the most relative utility is adopted. The overall utility index of a platform for a consumer is defined as the average of all individual utility indexes of the platform[3]:

$$I_{U_{ijt}} = \frac{\sum_{v=1}^{n_v} I_{U_{ijtv}}}{n_v} \ . \tag{2.}$$

In other words, the overall utility index of a platform is a linear combination of individual utility indexes, analogously to a typical linear regression model where a dependent variable is modeled as a linear

[3] What if all competing platforms are equally good in terms of the overall utility they can provide for a consumer, that is $\frac{1}{n_{jt}}\sum_{j=1}^{n_{jt}}\left(\frac{1}{n_v}\sum_{v=1}^{n_v} I_{U_{ijtv}}\right) = 1$? Such a situation is very unlikely to occur in practice, since the aforementioned equation is true if and only if: $\sum_{v=1}^{n_v} I_{U_{i1tv}} = \sum_{v=1}^{n_v} I_{U_{i2tv}} = \sum_{v=1}^{n_v} I_{U_{i3tv}} = \ldots = \sum_{v=1}^{n_v} I_{U_{in_{jt}tv}}$. For example, suppose the number of consumers on a platform is a value indicator: it is very unlikely for all competing platforms to have exactly the same number of consumers on them and the same prices simultaneously. Neither is it likely that when the number of consumers on each platform differs, the prices of each platform would differ in the exact same proportions (e.g., when two platforms compete, if a platform has twice as many consumers, but also twice the price of another platform, then the two platforms are equally good in terms of overall utility). Indeed, none of the alternative models to be presented resulted in a situation where competing platforms were considered equally good. Thus, considerations of how a consumer would behave in such a situation were excluded.

combination of the parameters[4]. From technical perspective, the form of the equation (2.) has several desirable properties especially when it comes to empirical validation. To begin with, it is flexible. One could add an arbitrary number of dimensions (i.e., utility indexes) to an alternative model, theory permitting, without changing the shared architecture. Further, empirical data can be easily used for parameterization as any utility indicators by which all competing platforms can be compared are usable. Finally, the alternative models based on the given architecture can be directly compared in terms of their predictive accuracy[5]. We note that our model design departs from formal models of platform-based or multi-sided markets (e.g., Rochet & Tirole, 2006; Weyl, 2010) but given our goal of descriptive accuracy, instead of analytical tractability, we feel that such departure is justifiable.

The agents act one at a time on a time step (i.e., at time t). In other words, the actions of agents are sequential. Consumer agents act after the platform providers and complementary product providers have acted. All preceding actions on a time step are potentially influential to subsequent actions on the same time step. Thus, consumer agents make their adoption decisions based on the latest available information.

3.2 Alternative models and assumptions

We test four alternative models based on four sets of theoretical assumptions that are summarized in Table 1. In a model, the overall utility index of a platform for a consumer comprises of two individual utility indexes, while the other utility index accounts for the direct network effect and the other accounts for the indirect network effect[6]. We introduce four different value indicators that operationalize the four alternative assumptions regarding consumer behavior. The first value indicator is for operationalizing selective attention, the second is for local bias, the third is for unselective attention, and the fourth is for global bias.

Table 1. The alternative models by which the alternative sets of theoretical assumptions are tested.

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[4] Here, the parameters are fixed (i.e., $\frac{1}{n_v}$), thus reducing the total number of parameters in the alternative models and hence mitigating the problem of overfitting them to data. It implies that all individual utility indexes affect the overall utility index of a platform equally. However, the importance of offering certain type of utility for the competitiveness of a platform depends endogenously on how much this type of utility all the competing platforms are offering.

[5] Obviously, one can always compare the predictive accuracy of different models even if they did not share the same basic structural form. However, these comparisons might not be "fair" in the sense that, especially when different modeling approaches are used, predictive accuracy might be constrained by the method itself. For example, system dynamics models cannot replicate diffusion dynamics arising from local direct network effects whereas agent-models can (Rahmandad & Sterman, 2008), and thus it is likely that agent-based models have the potential of being more accurate in predicting diffusion than system dynamics models. Therefore, fixing the method and model architecture makes alternative model comparison feasible.

[6] However, we do test how the results from Models 3 and 4 change when the local direct network effects are "switched off" (see Figure 2), because this enables the identification of the cause of the observed market outcome.

Assumptions	Unselective attention	Selective attention *(Assumption 1)*
Global bias	*Model 1* $I_{U_{ijt}} = \frac{I_{U_{ijt3}} + I_{U_{ijt4}}}{2}$	*Model 2* $I_{U_{ijt}} = \frac{I_{U_{ijt1}} + I_{U_{ijt4}}}{2}$
Local bias *(Assumption 2)*	*Model 3* $I_{U_{ijt}} = \frac{I_{U_{ijt2}} + I_{U_{ijt3}}}{2}$	*Model 4* $I_{U_{ijt}} = \frac{I_{U_{ijt1}} + I_{U_{ijt2}}}{2}$

3.2.1 *Selective attention*

The first value indicator is the perceived quality of complementary products on the platform (i.e., an indirect network effect). Consumers are assumed to be selectively attentive, as they tend to show more interest to newer as compared to older complementary products, although the newer may be inferior to older complementary products, which then affects the utility of a platform.

Call this value indicator V_{ijt1} (and the corresponding utility indicator U_{ijt1} and utility index $I_{U_{ijt1}}$). Let a binary variable a_{jkt} represent that a complementary product C_k is available on platform P_j at time t ($a_{jkt} = 1$, if available)[7]. The perceived quality of the complementary product at time t is denoted as $PQ_{kt} > 0$. For a consumer the value of a platform from the perspective of the perceived quality of complementary products is the average of all perceived qualities on the platform at time t:

$$V_{ijt1} = \frac{\sum_{k=1}^{n_{kt}} (PQ_{kt} * a_{jkt})}{\sum_{k=1}^{n_{kt}} a_{jkt}} \quad . \tag{3.}$$

The perceived quality of a complementary product is a function of its actual quality $Q_k > 0$ (actual quality is static[8]), and additionally it depends on the rate of change r_{Qt} in overall actual quality (i.e., an aggregate sum) of complementary products on the whole market (i.e., all platforms combined) at time t[9], and the time the product has been available in the market t_{kt} (in other words, its selling time) at time t. Let a binary variable N_{kt} represent that a complementary C_k is new to the market at time t, meaning its selling

[7] Note that we consider complementary products that are published on multiple platforms as separate products in technical terms (i.e., $\sum_{j=1}^{n_{jt}} a_{jkt} = 1$).
[8] It is not mathematically mandatory, and it may not be practically mandatory either that the actual qualities of complementary products are kept static, we just do not have longitudinal data of how the qualities of complementary products vary over time in our empirical setting.
[9] To clarify, the perceived quality of complementary products on a platform is affected by the introduction of new complementary product quality to all competing platforms.

time $t_{kt} = 0$ (then $N_{kt} = 1$; if $t_{kt} > 0$, then $N_{kt} = 0$). For a complementary product C_x $(x \in k)$, its perceived quality at time t is calculated in the following manner:

$$PQ_{xt} = \frac{Q_x}{\left(1 + r_{Qt}\right)^{t_{xt}}} = \frac{Q_x}{\left\{1 + \frac{\sum_{k=1}^{n_{kt}}(Q_k * N_{kt})}{\sum_{k=1}^{n_{kt}}[Q_k * (1 - N_{kt})]}\right\}^{t_{xt}}} \quad . \qquad (4.)$$

The perceived quality of a complementary product is dynamic. The greater the values of the rate of change in overall actual quality of complementary products in the market and the time a complementary product has been available in the market, the lower is the perceived quality of the complementary product, and vice versa. When there are no complementary products that are introduced to the market and/or when a complementary product is new to the market, its perceived quality is equal to its actual quality. The relative difference in perceived qualities of new and older products is at maximum when the rate of change in overall actual quality of complementary products in the market peaks, and the relative difference is smallest when no new products are introduced to the market.

Equation (4.) satisfies the given assumption of selective attention, while still being relatively simple. It captures the dynamics of how new information, that is, the introduction of new complementary product quality to the market draws the consumers' attention toward newer products. Given that newer products are as good (or even worse) as older products, the former are perceived to be better than the latter, particularly when the availability of high quality products in the market increases significantly. However, as is evident from the equation (4.), these effects are not dichotomous and they are endogenously determined by the agents' actions in the market. It follows that a platform should keep up with the competition in renewing the pool of complementary products and ensuring their quality[10].

3.2.2 Local bias

The second value indicator is the number of those connections of a consumer who have adopted a platform (i.e., direct network effect). Here, consumers are assumed to base their platform adoption decisions partly on the platform adoption decisions of their connections, but not on the adoption decisions of all of the other consumers, thereby possibly making them locally biased.

[10] Equation (4.) also captures the issue of multi-platform complementary products making competing platforms more equal in terms of perceived quality (see e.g., Corts & Lederman, 2009). That is, a consumer adopting at time *t* evaluates competing platforms more equally the more multi-platform complementary products are being introduced to the market at time *t*, given the new (multi-platform) releases receive more weight than the preceding releases in calculating the average of perceived quality of complementary products on a platform.

We refer to this value indicator as V_{ijt2} (and the corresponding utility indicator as U_{ijt2} and utility index $I_{U_{ijt2}}$). Let a binary variable c_{xi} represent that a consumer E_x ($x \in i$) is connected to another consumer E_i ($c_{xi} = 1$, if connected), and a binary variable a_{ijt} represents that the consumer E_i has adopted a platform P_j ($a_{ijt} = 1$, if adopted) at time t. To clarify, for consumer E_x, the value of a platform from the perspective of how many of the connections have adopted the platform is calculated in the following manner:

$$V_{xjt2} = \sum_{i=1(i \neq x)}^{n_{it}} (c_{xi} * a_{ijt}) \quad . \tag{5.}$$

Hence, the network structure between consumers must be defined. Here, we briefly present the mathematical properties of the Watts and Strogatz (1998) model. The model begins with a ring lattice, a graph where all M nodes are connected to $n_{c_{avg}}$ number of neighbors (i.e., the mean degree, which is assumed to be an even integer), with each side of the node having an equal number of neighbors (i.e., $\frac{n_{c_{avg}}}{2}$). Then, for each node at a time, the algorithm rewires the connections so that the probability of changing an existing connection between E_x and E_y $(x, y \in i)$ to a non-existing (i.e., $i \neq y$ and $c_{ix} = 0$) connection between E_x and E_i is $\Pr(c_{xi})$, which is a constant. For clarity, denote $\Pr(c_{xi})$ as P_r. When $0\ \% < P_r < 100\ \%$, the algorithm produces a network with small-world properties; when $P_r = 100\ \%$, the algorithm produces a random network; and when $P_r = 0\ \%$, the algorithm produces a regular network. As the value of P_r approaches 100 %, the network becomes more random; and when it approaches 0 %, the network becomes more regular. This model enables testing how various strengths of local bias affect consumers' adoption decisions by varying the values of $n_{c_{avg}}$ and P_r. Based on Lee, Lee and Lee (2006), we assume to find out that the predictive accuracy is maximized when the generated network exhibits small-world properties (i.e., high clustering and short characteristics path length) that preserves local bias.

Now that we have introduced a networked consumer side of the market, the question is, in which order do they adopt platforms? We choose not to impose a correlation between social connectivity and adoption timing [11]. That is, we distribute adoption times randomly to consumers, while controlling for how

[11] Some researchers (e.g., Goldenberg, Han, Lehmann, & Hong, 2009) have found evidence that the likelihood of adopting a new product early is positively related to the strength of social connectivity (i.e., how many connections a consumer has). If it exists, this effect could probably be due to that the more connected a consumer is, the more probable it is that he/she will be exposed to social stimuli that trigger adoption decisions earlier. However, investigating the effect that the strength of social connectivity has on adoption time and, thus, selection of a platform would require us to impose a correlation between social connectivity and adoption time, and test how various strengths of this correlation affects the results (because our data determines how many consumers are adopting at each time).

many consumers are adopting at each time based on data. This is done simply so that the consumer network is generated first, and for each time step, the given number of adopting consumers is drawn randomly from the entire consumer population. To clarify, this process is analogous to drawing cards from a deck: each card (i.e., a consumer) is drawn randomly from the deck (i.e., the entire consumer population), thereby resulting in a random sequence (where each subsequence represents an adoption time) of the ranks and suits (i.e., the predetermined characteristics of the consumers, that is, the connections among consumers).

3.2.3 Unselective attention and global bias

In contrast to the first value indicator, the third value indicator is based on the assumption that consumers are unselectively attentive. That is, they perceive the qualities of complementary products as they truly are, so the introduction of new product quality to the market does not alter one's perception of quality. Calculating V_{ijt3} is almost identical to calculating V_{ijt1}, the only difference being that the quality variable in equation (3.) is the actual quality, not the perceived quality. In other words, V_{ijt3} is the average quality of complementary products on the platform at time t.

Analogously, in contrast to the second value indicator, the fourth value indicator is based on the assumption that consumers are not locally but globally biased. That is, they value global direct network effects (i.e., the general connectivity of the network) and thus V_{ijt4} is the number of consumers on the platform. In effect, no consumer network needs to be generated, since general connectivity determines adoption decisions.

3.3 Test setup

3.3.1 Description of the empirical case and boundary conditions of our study

Our empirical setting concerns the competition between two video game console platforms, namely PlayStation 3 (Sony) and Xbox 360 (Microsoft). Both of the video game consoles are targeted to high-end gamers and thus, to relatively homogeneous consumers what comes to their preferences regarding the video game console. If to compare PlayStation 3/Xbox 360 and Nintendo Wii for example, the customer groups targeted would differ: PlayStation 3 and Xbox 360 were targeted to high-end gamers whereas Nintendo Wii was targeted toward casual gamers.

We feel it would make the analysis unnecessarily complex in this paper. Moreover, we do not know the nature of this correlation (i.e., whether it is linear or nonlinear), or if it even exists. Due to this, the correct method to analyze this effect is not to impose a correlation, but to let consumer agents decide on when to adopt based on their connections' decisions. In other words, it is to model the diffusion of platforms (i.e., diffusion of the entire category of platforms), and we argue that this is a separate question from what we are studying in this paper, and thus it deserves an independent in-depth analysis.

More specifically, our study conforms to the following boundary conditions. Firstly, we focus on the competition between two incompatible platforms, meaning that we do not study competition between providers of those platforms (Sony and Microsoft). For this reason, we do not for example consider how the previous generation of platforms affects the competition between subsequent generations of platforms and further, the competition between platform providers (e.g., possibly explained by brand loyalty).

Secondly, the aim of our study is to develop a simulation model that can be tested with empirical data. This aim necessarily narrows down the set of parameters we can incorporate in our model, as we must be able to access data for all of the incorporated parameters. Thus, we exclude parameters such as brand loyalty and hardware quality from our consideration. Beyond data limitations, we also expect that brand loyalty and hardware quality were not among the primary explanatory factors in this particular empirical case and/or that our model captures the latter effect in part, even if present. Thus, we argue that the empirical case is a suitable one for our theory development. First, as the two consoles were basically backward incompatible with their predecessors (Microsoft, 2015; Sony, 2015), brand loyalty arising from network effects should not be a factor. Second, we presume the two consoles were largely similar in hardware, because the majority of games were released for both consoles according to data. This could not have been possible if the hardware quality differences were substantial—for example, the previous generation of a console is rarely capable of running games developed for the subsequent generation, because of the insufficient hardware (apart from the imposed technological incompatibility). On the other hand, anecdotal evidence suggest Xbox 360 was slightly inferior to PlayStation 3 in hardware quality. However, most games were unexpectedly released for Xbox 360, given hardware quality should positively correlate with the provision of games to a console (Gretz, 2010)—making it unclear whether the hardware quality differences between the two consoles were substantial. Nevertheless, should there have been any hardware quality differences, they are on the other hand indirectly taken into consideration in our model. That is, as we model how consumer agents perceive the quality of complementary products, we believe that this parameter captures the hardware quality indirectly (i.e., better hardware enables making technologically better games). The literature is consistent when it comes to the complementary products and their qualities being among the primary determinants of platform adoption (see e.g., Binken & Stremersch, 2009; Corts & Lederman, 2009; Kim et al., 2014). It is thus safe to assume console hardware is most useful to consumers when it is utilized for gaming.

Thirdly, our focus is on the decision-making of consumer agents at the time they make the decision of which video game console to adopt. The adoption decision of the consumer agent focuses solely on how the video game console is evaluated in terms of playing video games with the console. We acknowledge that modern video game consoles might be purchased for other reason than playing video games (e.g., watching movies), but in our study, the consumer agents only focus on playing video games with the console. Furthermore, we do not model the decision-making of supplier agents (video game developers) or platform providers, such as Sony or Microsoft in our study.

3.3.2 Description of the data

The empirical data includes console and game launch times, sales and prices for the consoles over time, and game qualities. After consolidation and transformations, the data enable us to observe the competition between the two consoles from November 2005 to June 2013, on a monthly level.

All data were retrieved from the Web. Console launch times were checked directly from the manufacturers' sites, and sales and price data were obtained from multiple technology news sites, which in turn have collected the data either directly from the console providers or from various sources like archived department store catalogs. Console launch times differ slightly by region, but initially Xbox 360 was launched on November 22, 2005, and PlayStation 3 was launched on November 11, 2006. The global console sales (in units sold) are reported quarterly. Console prices (in dollars) are reported annually[12].

For data on game launch times and quality, we use Metacritic (www.metacritic.com) as the source. Metacritic is arguably the most comprehensive and objective source for game reviews. It consolidates individual and professional game reviews from multiple professional reviewing websites. Process description of Metacritic's review consolidation resulting into a product-specific Metascore is available online.[13] We treat the actual quality of a game simply as the Metascore value given to it, which is the weighted average value of individual reviews from professional sites (i.e., some reviews have more weight than others, based on the quality of the review and its overall stature), ranging from 0 to 100. Representing a form of archival records data (cf. Williams and Shepherd, 2015), Metacritic can still be considered to represent a new type of a source of data. It has nevertheless been used in previous research to measure both game quality (Kim et al., 2014) as well as the perceived quality of music albums (Waldfogel 2011), for example. All game launch times are reported on a daily level in Metacritic. After excluding the games that did not have a Metascore and those that were published after June 2013, the data included game reviews for 2 074 games published on PlayStation 3 and Xbox 360.

Due to the differing time intervals of measurement, all data are transformed to a monthly level. Monthly level is arguably the smallest acceptable time unit to which the data could be transformed without strong biases, and it is desirable to use as small a time unit as possible in order to simulate adoption dynamics accurately. With regard to the console sales data, the quarterly sales are distributed evenly to a monthly level, except for the first quarter after the launch of each console, where the sales are distributed

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[12] We assume that the U.S. prices for the consoles approximate their global prices, thus using the former as input to the alternative models should not distort the results.
[13] "How We Create the Metascore Magic," http://www.metacritic.com/about-metascores

evenly between November and December. With regard to console prices, changes in pricing between consecutive years resulted in equal changes on each month during the year. In other words, in both cases, we assume linear changes between data points. While we cannot show this data-related assumption is realistic, it is the simplest one. When there is a lack of data, fitting more complex functions to the data is arguably unjustifiable. Actually, if the models are able to predict adoption decisions with poor data, it shows that the results are not so sensitive to the errors in data. In such a case, we expect that the predictions would only improve if more high quality data were used. Finally, the game launch times are aggregated from the daily level to the monthly level. That is, we consider that all games published within a month have been published at the same time. Figure 1 visualizes the empirical data after these transformations.

Figure 1. Visualization of the empirical data.

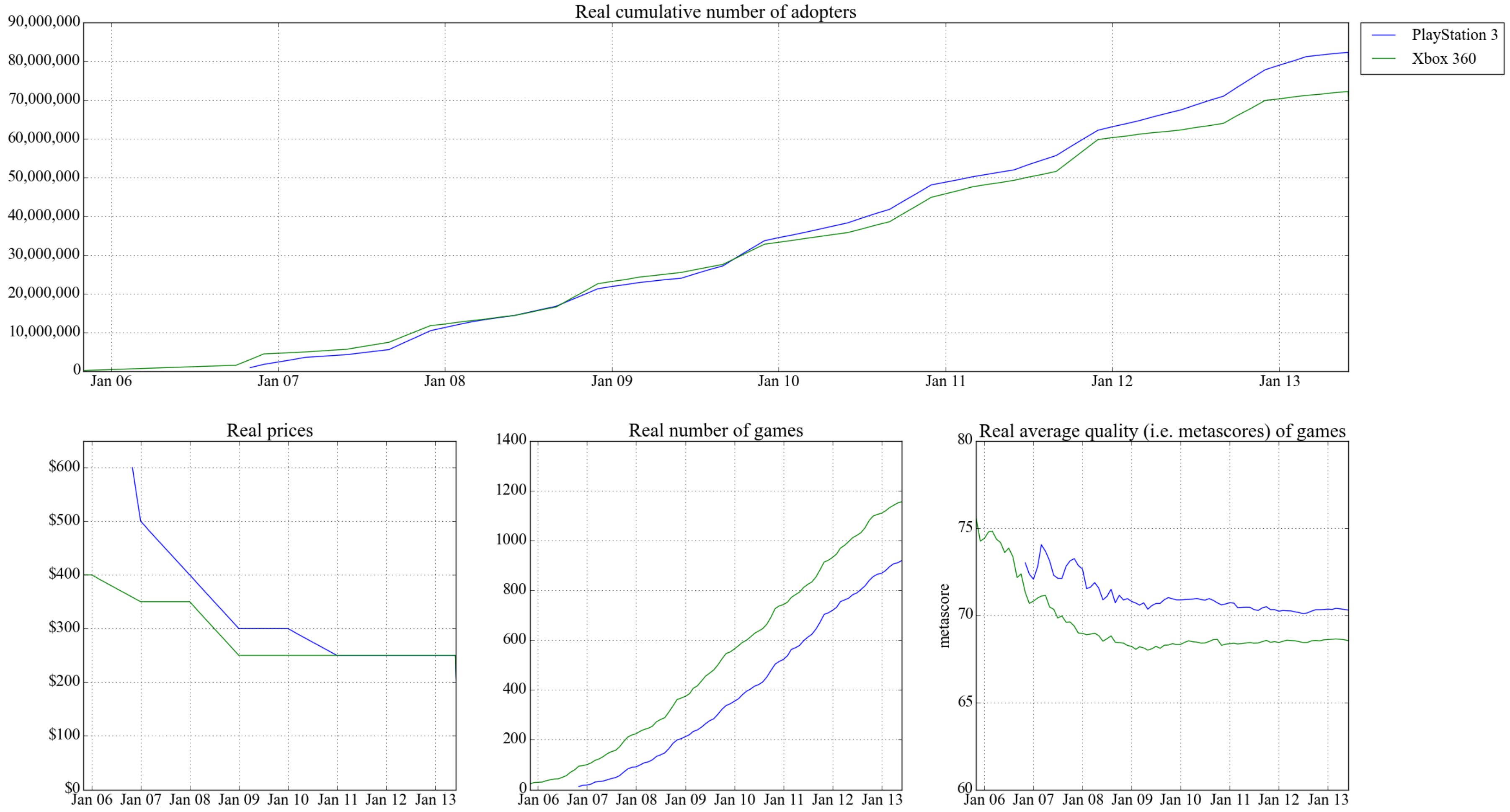


Figure 1 clearly shows that Xbox 360 had the potential competitive advantage due to being the early entrant, having greater installed base initially, greater pool of complementary products throughout the observed life-cycle of the consoles, and a lower initial price. Although PlayStation 3 had slightly better games on average, it is not clear why PlayStation 3 obtained most adopters eventually. In light of the WTA hypothesis, Xbox 360 should have obtained most adopters, if not all of them.

3.3.3 Parameterization

The launch times of consoles and games, pricing of consoles and actual qualities of games are taken as input parameters and variables to the alternative models being simulated. In effect, a simulation begins in November 2005 and ends in June 2013, and a time step is one month. We test each model incorporating local direct network effects (i.e., Models 3 and 4) with several combinations of the two Watts & Strogatz model parameters, $n_{c_{avg}}$ and P_r. Note that since only the network structure between consumers is controlled exogenously and stochastically, the alternative models that do not take local direct network effects into account (i.e., Models 1 and 2) are all completely deterministic, thereby not requiring multiple simulation iterations and sensitivity analysis.

Further, we use agent sampling in order to obtain a statistically feasible sample of iterations for each parameter combination: that is, one consumer agent represents multiple real consumers. Therefore, the predicted number of adopters for a platform is calculated as the number of consumer agents who have adopted the platform multiplied by the number of real consumers an agent represents. It is acknowledged that this sampling procedure may affect the results. Therefore, we vary the number of consumer agents to the degree that is practically possible[14]. We divide the execution of models into three stages: first, we run the "whole" (i.e., chosen) parameter space and all alternative models with the base number of agents; second we run the alternative models with restricted parameter space, while doubling the number of agents; finally, we run the most accurate alternative model with the optimal parameters derived from the previous runs, while increasing the number of agents gradually. In the first stage, when using the base number of agents, we use the following values for the network parameters: $n_{c_{avg}} = \{2, 4, 6, \ldots, 98, \text{and } 100\}$, and $P_r = \{0\ \%$, 0.01 %, 0.02 %, 0.03 %, …, 0.09 %, 0.1 %, 0.2 %, 0.3 %, …, 90, 100 %} (i.e., logarithmic scale). The base number of agents is 10 000, thereby implying that one agent represents approximately 15 434 real consumers (given the number of consumers was 154 340 000 in total, according to data). In the second stage, we restrict the network parameter $n_{c_{avg}}$ to {2, 4, 6, …, 38, and 40}, while using the same values for

[14] If the number of consumer agents in a simulation equals the real number of consumers in the market, executing the alternative models becomes extremely slow, if not impossible, due to the restrictions in computing power and memory. We have tried our best in ensuring computational efficiency, and through carefully evaluating the effects of agent sampling on results, we mitigate these technical problems.

P_r as before. In the third and final stage, we simulate with 10 000, 15 000, 20 000, …, 95 000, and 100 000 agents.

For Models 3 and 4, we run 500 iterations for each model parameterization. In other words, for each parameter combination in each of these alternative models, 500 iterations are run. In effect, we simulate several million models in total. All parameters and variables that have been presented in the methodology section are summarized in Table 2.

Table 2. Summary of the parameters and variables used in the alternative models.

Parameter or variable	
E_i	ith consumer
$*n_{it}$	number of consumers in the market at time t
P_j	jth platform
$*n_{jt}$	number of platforms in the market at time t
$*p_{jt}$	price of P_j at time t
C_k	kth complementary product
$*n_{kt}$	number of complementary products in the market at time t
$*a_{jkt}$	binary variable representing that C_k is available on P_j at time t
$*Q_k$	actual quality of C_k
$*PQ_{kt}$	perceived quality of C_k at time t
$*t_{kt}$	amount of time for which C_k has been in the market at time t
$*N_{kt}$	binary variable representing that C_k is new to the market at time t
$*r_{Qt}$	change in the overall actual quality of complementary products in the market at time t
$n_{c_{avg}}$	average number of connections for consumers (Watts & Strogatz, 1998)
P_r	probability of rewiring an existing connection among consumers (Watts & Strogatz, 1998)
c_{xi}	binary variable representing that E_x ($x \in i$) and E_i are connected
a_{ijt}	binary variable representing that E_i has adopted P_j at time t
n_v	number of value indicators for platforms
V_{ijtv}	vth value indicator of P_j for E_i at time t
U_{ijtv}	vth utility indicator P_j for E_i at time t
$I_{U_{ijtv}}$	vth utility index of P_j for E_i at time t
$I_{U_{ijt}}$	overall utility index of P_j for E_i at time t

* Parameterized / calculated solely based on real data.

3.3.4 Test statistics

First, we measure the predictive accuracy of each alternative model. The predictive accuracy of a model is determined by the sum of the squared errors in predicting cumulative number of adopters on each competing platform over time. Formally, prediction error equals $\sum_{t=t_0}^{n_t} \sum_{j=1}^{n_{jt}} (y_{jt} - f_{jt})^2$, where t_0 is the start time of measuring prediction errors, y_{jt} is the real number of adopters on platform P_j, and f_{jt} is the predicted number of adopters on the platform at time t. The model having the lowest prediction error on average is considered the most accurate. Because PlayStation 3 was launched approximately a year after Xbox 360, and no other competing platforms are being observed, it is reasonable to begin measuring prediction errors only after PlayStation 3 was launched (i.e., before the launch of PlayStation 3 all consumers will adopt Xbox 360, obviously). Therefore, measuring prediction errors began in November 2006.

Second, a model must be able to explain why a late entrant platform (PlayStation 3) was adopted by most consumers at the end of the observed market life cycle. Due to the stochastic nature of some alternative models, we use the proportion of iterations (i.e., a probability) when PlayStation 3 obtained most adopters eventually as the other measure for explanatory power (for deterministic models, the value is either zero or 100 %).

4 RESULTS

4.1 Main results

Table 3 presents the descriptive statistics for the alternative models with their optimal parameters. Model 4 is the most accurate in terms of predictions, and even its most inaccurate prediction is more accurate than the most accurate prediction of Model 3 that, on average, is the second most accurate model. The difference in the average prediction errors of the most inaccurate models (Models 1 and 2) and Model 4 is approximately -99.86%, which is a highly substantial difference. Although Model 3 performs substantially better than Models 1 and 2 in terms of average prediction errors (-21.69 %), it did not result in PlayStation 3 obtaining most adopters in single simulation iteration. Model 4 was the only one that resulted in PlayStation 3 obtaining most adopters: the proportion of iterations when PlayStation 3 obtained most adopters was 94.4 % (-3.2 %, $+2.3$ %)[15]. Although not being closer to 100%, the next section (4.2) will show that it was not by chance that PlayStation 3 obtained most adopters in Model 4 with the optimal parameters.

[15] We use Clopper-Pearson confidence interval for binomial distribution, with $\alpha = 1$ %.

Table 3. Descriptive statistics for the alternative models with their optimal parameters when the number of consumer agents is 10 000.[16]

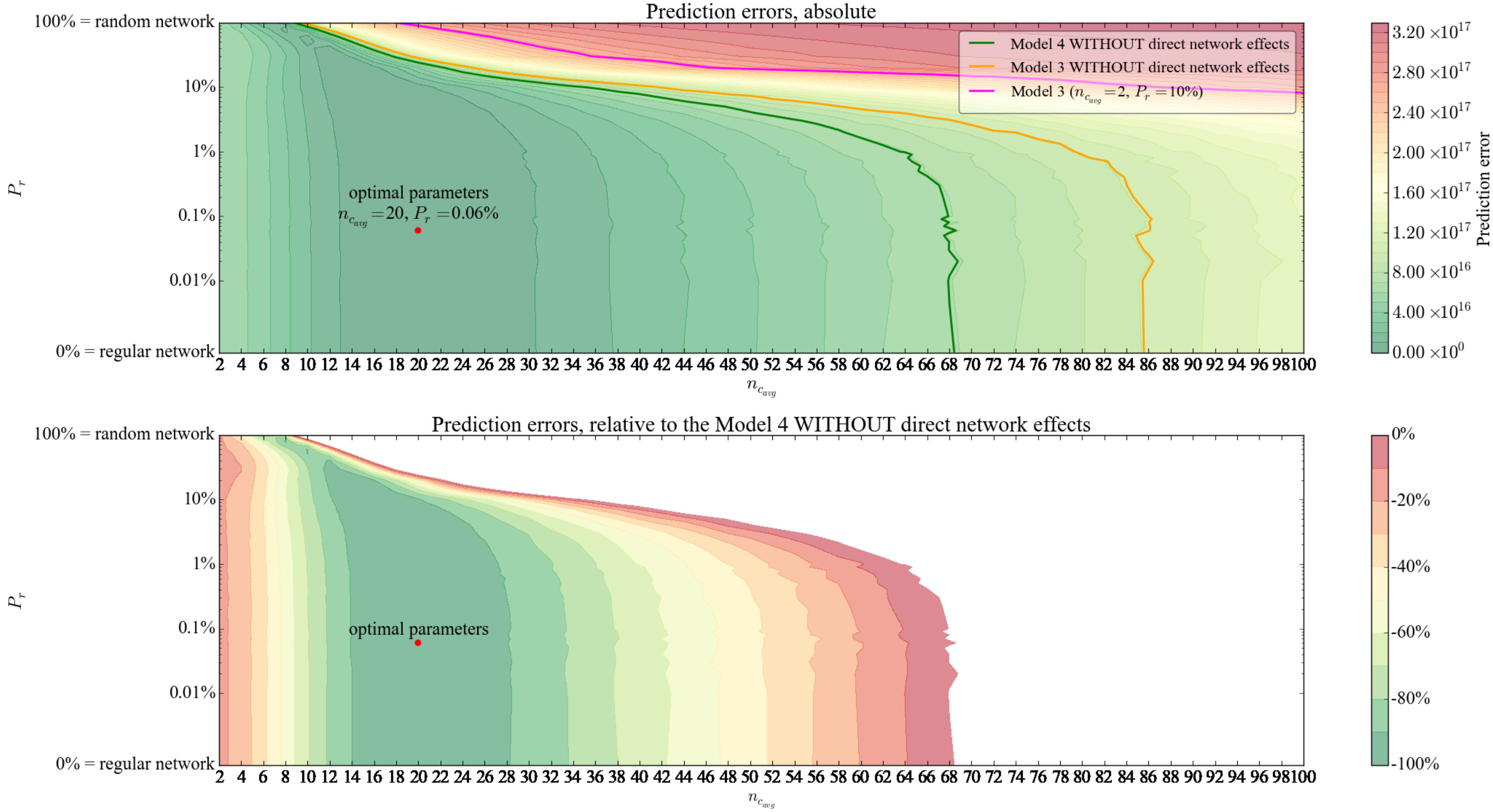
	Model 1*	**Model 2***	**Model 3**** ($n_{c_{avg}} = 2$, $P_r = 10$ %)	**Model 4**** ($n_{c_{avg}} = 20$, $P_r = 0{,}06$ %)
Absolute average prediction error	3.27×10^{17}	3.27×10^{17}	2.56×10^{17} ($min. = 2.48 \times 10^{17}$, $max. = 2.65 \times 10^{17}$)	4.53×10^{14} ($min. = 4.58 \times 10^{13}$, $max. = 3.79 \times 10^{15}$)
Relative difference (to the worst model) in average prediction error	0 %	0 %	-21.69 % ($min. = -24.25$ %, $max. = -19.02$ %)	-99.86 % ($min. = -99.99$ %, $max. = -98.84$ %)
Proportion of iterations when PlayStation 3 obtained most adopters	0 %	0 %	0 %	94.4 %

* n = 1, i.e., the model is deterministic and there are no exogenous parameters.
** n = 500.

Figure 2 illustrates the average prediction errors of Model 4 in relation to the small-world network parameters in a two-dimensional contour plot. Further, the average prediction error of the second most accurate model (Model 3, with its optimal parameters) is shown as a reference level on the contour. Further, we tested how the predictions of Models 3 and 4 changed when local direct network effects were “switched off”, and these results are also presented as reference levels on the contour.

[16] Given we observe and predict demand for several tens of months and as the observed demand for the two consoles were measured in tens of millions of users—thus the absolute prediction errors can be millions of users for a console at a month—the sum of all squared prediction errors literally blows up (e.g., an absolute prediction error of a million users implies 10^{12} addition to the sum of squared errors; see section 3.3.4). That is, the absolute average prediction error is “just a number” that is not that easy to evaluate alone, but the relative differences in average prediction errors or deconstructing the metric tells more clearly about the predictive accuracy—for example, the prediction error of $4.53 * 10^{14}$ implies that the absolute prediction error for a console at a month tends to be about 1.68 million users (assuming the prediction error remained constant).

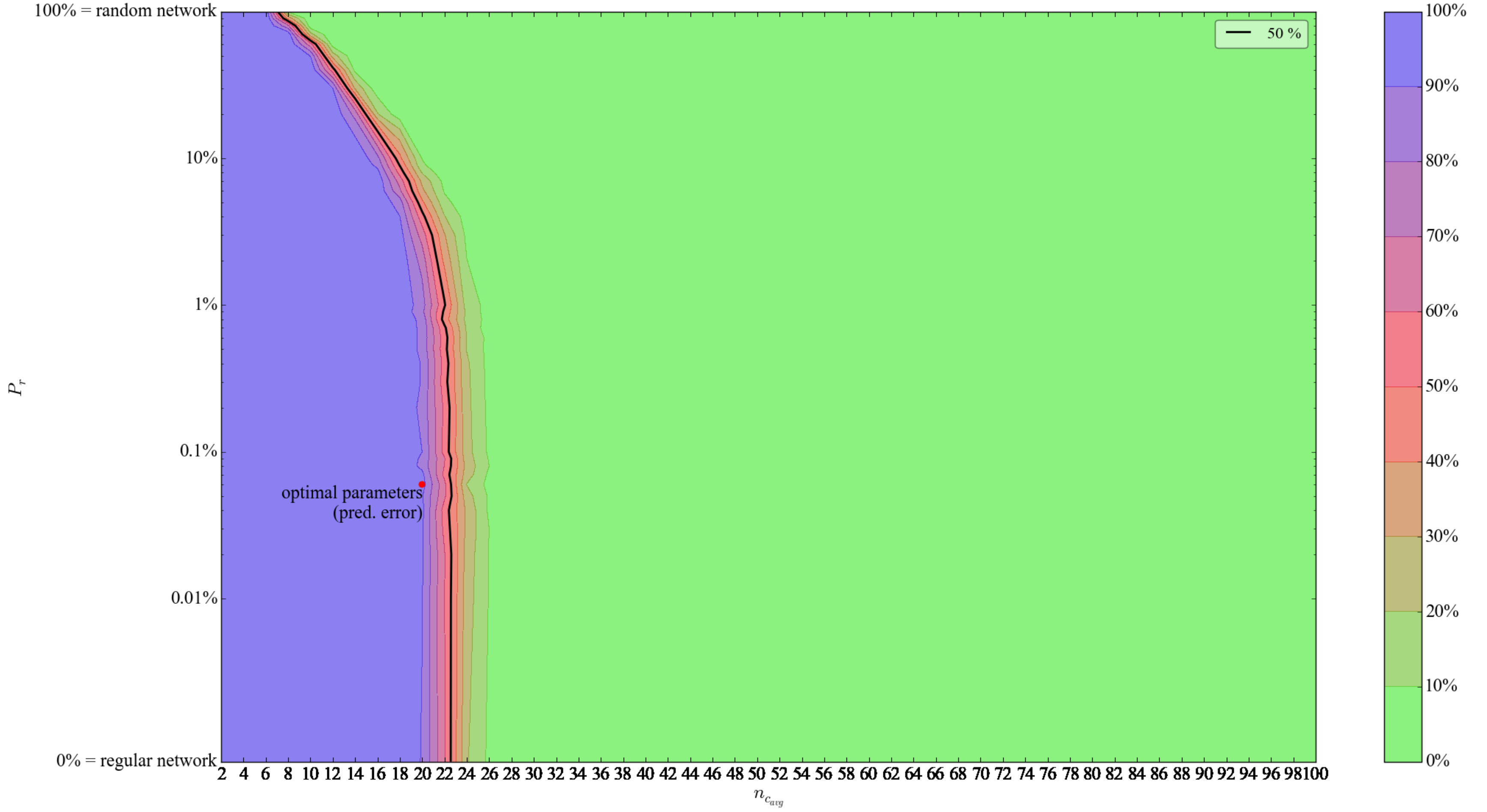
Figure 2. Average prediction errors of Model 4 in relation to the small-world network parameters $n_{c_{avg}}$ and P_r, and including average predictions of selected (most accurate) alternative models as reference. Note that the reference predictions indicate certain levels on the contour. The number of consumer agents in the models is 10 000.



First, Figure 2 illustrates how Model 4 is more accurate the lower the average number of connections for the consumers is. However, the optimal value for $n_{c_{avg}}$ $(= 20)$ suggests that the number of influential connections is relatively small (i.e., not in the extreme). When $n_{c_{avg}}$ is relatively small, few connections through which direct network effects can be leveraged exist in general, thereby preserving local bias. Second, the prediction errors are sensitive to the network structure. The global minimum is reached when the network exhibits small-world properties, since the optimal value of P_r $(= 0{,}06$ %) is not zero or one. In fact, the optimal value of P_r suggests that the network is more regular than random. The more regular the consumer network is, the higher the average number of connections for the consumers can be before the prediction errors of Model 4 are greater than those of Model 3. These findings are in line with Lee, Lee, & Lee (2006), who showed that a highly clustered network (i.e., when P_r is relatively low (Watts & Strogatz, 1998, p. 441)) preserves local bias. Further, Figure 2 illustrates that Model 4 is significantly more accurate, when the local direct network effects are accounted for compared to when they are not (the difference in average prediction errors being -99.35 % at most). However, the same is not true for Model 3 as the average prediction errors are lower when local direct network effects are not accounted for compared to when they are taken into account.

Next, Figure 3 depicts the sensitivity of the market outcome (i.e., the proportion of iterations when PlayStation 3 obtained most adopters) to the network parameters in Model 4. It is evident that consumers must have had a relatively low number of connections to begin with so that it can be explained why PlayStation 3 obtained the most adopters. However, even if the prediction errors are "acceptable" (i.e., lower than those of Model 4 without direct network effects) with greater than the optimal value for the average number of connections ($n_{c_{avg}} = 20$), the probability of PlayStation 3 obtaining most adopters falls rapidly after increasing $n_{c_{avg}}$ beyond its optimal value. Thus, the acceptable parameter space is narrowed. However, the more regular the consumer network is, the greater the average number of connections can be until the probability for PlayStation 3 obtaining most adopters falls to the realm of chance.

Figure 3. The proportion of iterations when PlayStation 3 obtained most adopters in relation to the small-world network parameters $n_{c_{avg}}$ and P_r in Model 4. The number of consumer agents in the model is 10 000.



Finally, we report that assuming consumers only as selectively attentive (i.e., no other theoretical assumptions) does result in PlayStation 3 obtaining most adopters. Despite this, as is evident from Figure 2, the predictions are inaccurate (because the demand for PlayStation 3 overshoots significantly). We also report that the market outcome could not have been predicted if consumers were assumed to be unselectively attentive only, although this resulted in lower prediction errors than when local direct network effects were accounted for in this model. These further analyses imply that the reason for PlayStation 3 obtaining most adopters was its superior perceived quality. Direct network effects did compensate Xbox 360 for the competitive advantage that PlayStation 3 had in terms of perceived quality, but still enabled the late entrant to penetrate the market due to local bias. If the consumers were not locally biased, the advantage of PlayStation 3 in terms of perceived quality would not have been enough to compensate for its disadvantage in terms of global direct network effects. Obviously, neither global nor local direct network effects could have compensated for the disadvantage PlayStation 3 had if it came to the actual qualities of complementary products.

Overall, the results show that it is crucial for our explanatory ability to make both the selective attention and local bias assumptions in tandem. Changing either the selective attention assumption or the local bias assumption to an alternative set of theoretical assumptions, or ignoring either, implies that it is not possible to explain adoption as accurately as when both assumptions are in place.

4.2 Robustness checks

The effect of increasing the number of consumer agents (from 10 000 to 20 000) on prediction errors in Model 4 is shown in Figure 4. The average prediction errors are lowered the most with the parameters that follow the two minimum average error lines (representing each parameter with which the minimum average prediction error is obtained when the other parameter is fixed), which we refer to as suboptimal parameters. Further, the optimal parameters remain unchanged and the suboptimal parameters are relatively stable. In addition, Figure 5 reveals that it is more unlikely that PlayStation 3 obtained most adopters by chance with optimal and suboptimal parameters when increasing the number of consumer agents. Thus, we are more confident that the behavior of the model is predictable with optimal and suboptimal parameters. However, it should be noted that with most nonoptimal parameters, the prediction errors did increase and the probability for PlayStation 3 to obtain most adopters decreased unexpectedly; however, this is arguably not a problem since these parameters were neither optimal nor suboptimal. Thus, the “acceptable” parameter space (i.e., where the behavior of the model is predictable) narrows down to the suboptimal parameters. Further, we report that increasing the number of consumer agents did not improve the performance of other alternative models so that they would have been able to explain the market outcome and thus their results are not shown for clarity.

Figure 4. Change in average prediction errors of Model 4 when increasing the number of consumer agents from 10 000 to 20 000.

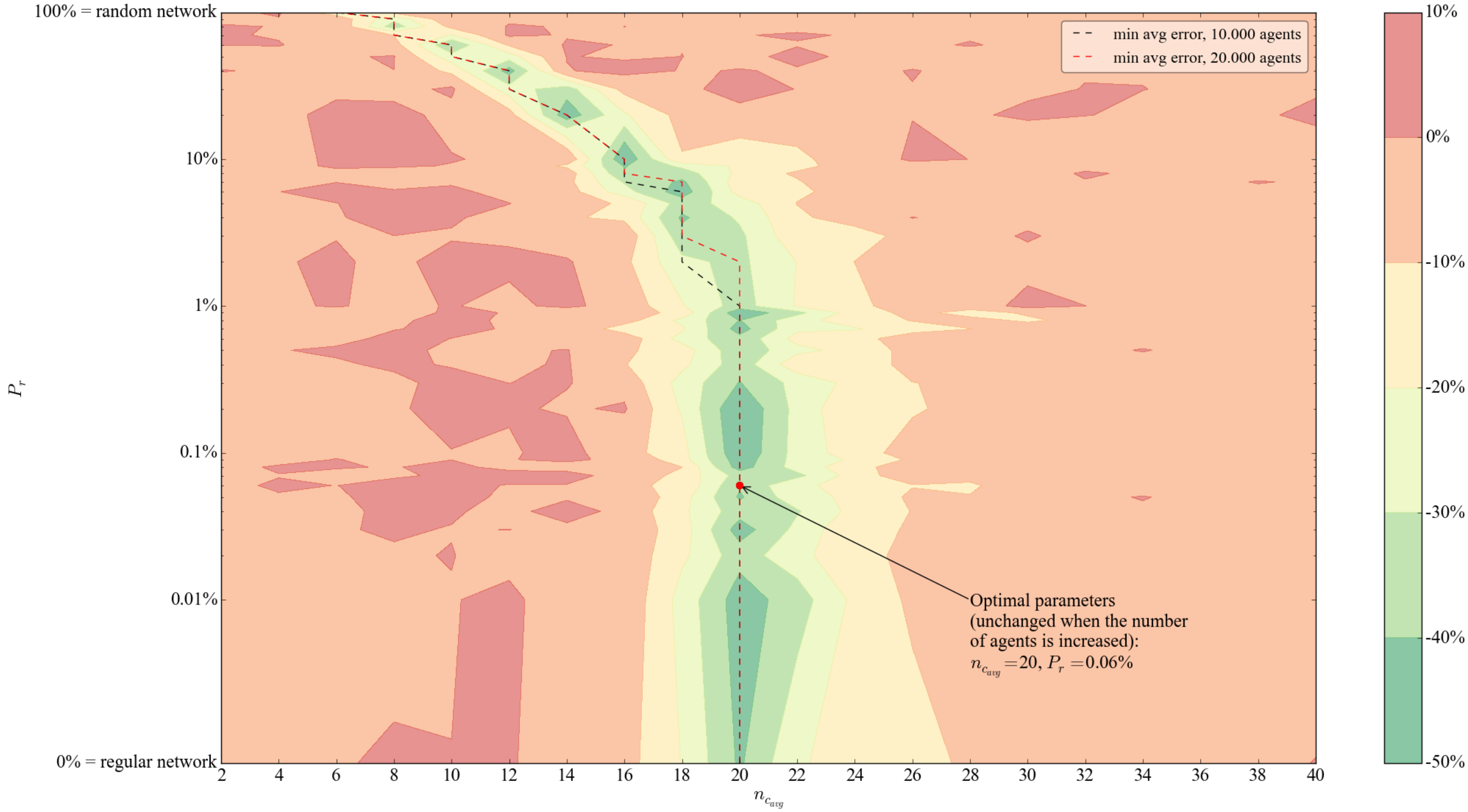
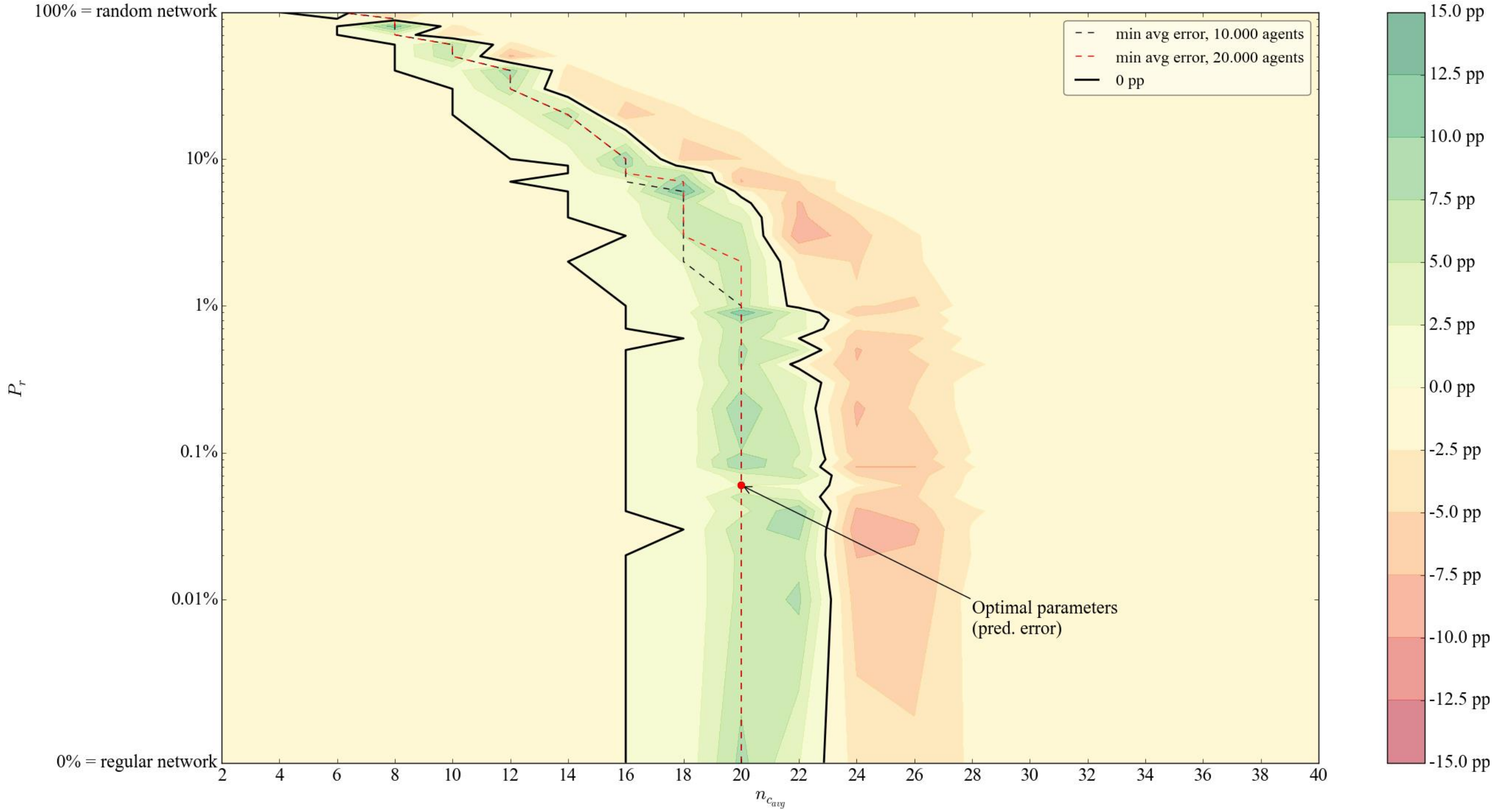


Figure 5. Difference (percentage points) in the proportion of iterations when PlayStation 3 obtained most adopters in Model 4, when increasing the number of consumer agents from 10 000 to 20 000.



In addition, we report that both the average prediction errors are reduced and the error range is narrowed significantly when gradually increasing the number of agents to 100 000 agents. However, the reductions in prediction errors become increasingly smaller, which is actually expected since all models have a limit to their explanatory power. These findings give even stronger support for the argument that the behavior of the model is predictable with the optimal parameters.

Finally, Figure 6 presents the most accurate predictions of Model 4 (i.e., when $n_{c_{avg}} = 20, P_r = 0.06$ %) when using the maximum number of consumer agents in this study (100 000). It is evident that the explanatory power of Model 4 is significant[17]. Further, not single simulation iteration resulted in PlayStation 3 having a lower number of adopters than Xbox 360 now (i.e., compared to the baseline presented in Table 3). Thus, it is not by chance that PlayStation 3 obtains most adopters in this model with the optimal parameters. This reduction in randomness illustrates how the inherent structure of the consumer network leads to relatively stable market outcomes, despite the fact that exact connections and adoption times were stochastically altered. In summary, we argue the sampling procedure related to how many real consumers a consumer agent represents in a model is justified.

To conclude, the results lend support to the selective attention and local bias being explaining factors to platform market sharing. Nevertheless, unobserved factors such as brand loyalty and hardware quality might have affected console adoption, although we reasoned for their absence in this particular empirical case (see section 3.3.1). We cannot obviously assess the bias due to the exclusion of explanatory variables other than indirectly; that is, given the predictive accuracy of Model 4, we maintain that it is unlikely the results were completely due to chance.

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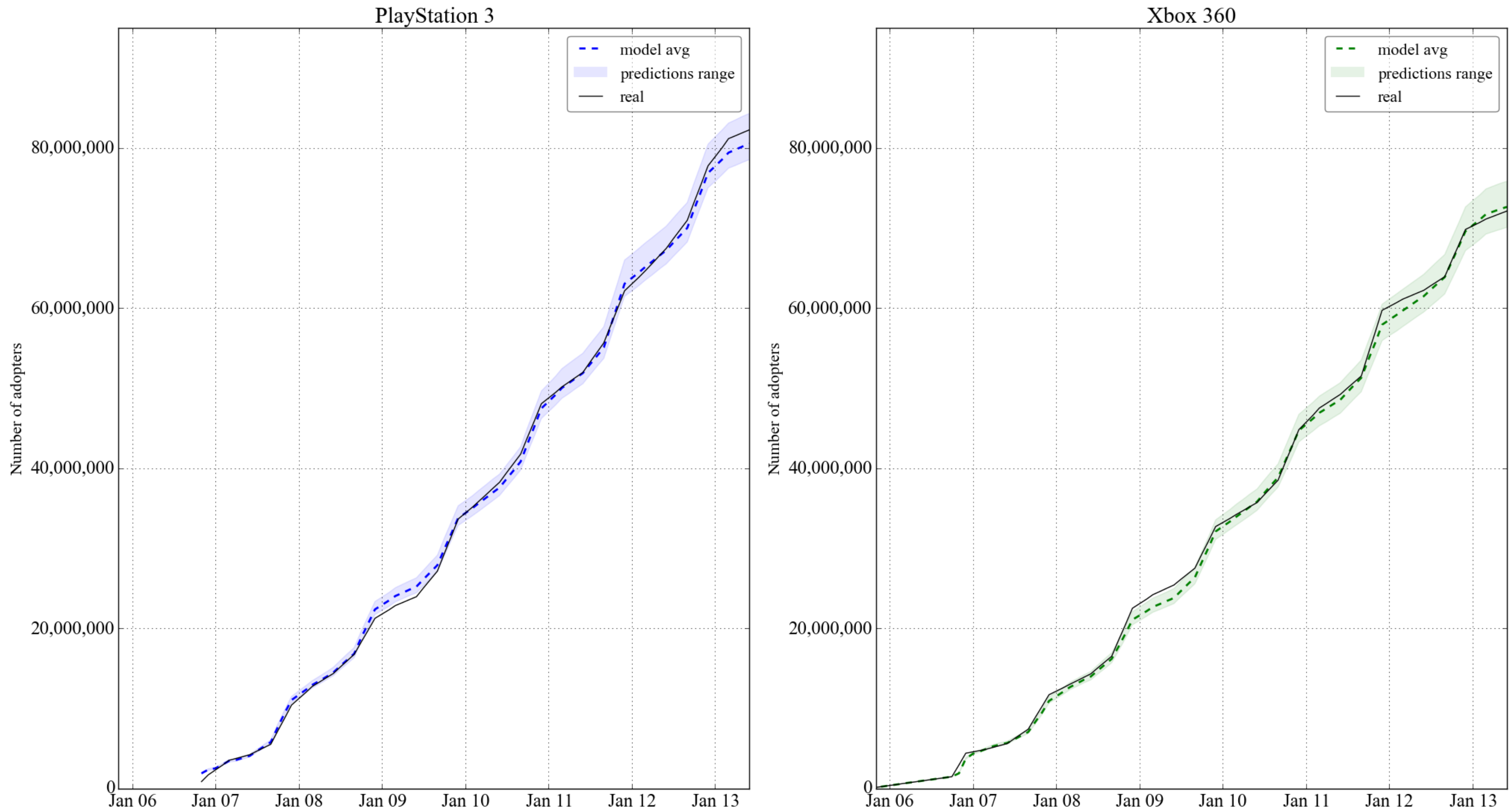
[17] We also employed OLS regression to test whether the most accurate predictions of Model 4 (i.e., when using 100 000 consumer agents and with the optimal parameters) correlated with real data. That is, we tested the regression model $y = \alpha * x$, where y are real data ($n = 172$) and x are predicted values. In effect, we could determine the significance level of Model 4, that is, whether the correlation between its predictions and real data was not due to chance. We find that with $p < 0.001$ ($F = 4324$), the predictions of Model 4 correlate with real data ($R^2 = 0.962$). Further, the predictions are relatively unbiased, since the regression coefficient is $\alpha \approx 1$ ($= 0.9922$). Thus, we conclude that it is very unlikely that Model 4 correlates with real data by chance. It must be noted that we compared changes in the cumulative number of adopters (i.e., monthly number of adopters), because comparing predictions and real data in cumulative number of adopters resulted in significantly non-normally distributed residuals due to strong autocorrelation. In addition to the problems related to autocorrelation, we acknowledge that unlike in typical regression analysis, this approach does not allow us to determine whether individual predictors (relating to the individual utility indexes in the model) are statistically significant. Yet, in simulation, sensitivity analysis serves as the method to determine the impact of individual predictors on predictive accuracy.

Figure 6. The most accurate predictions of Model 4 ($n_{c_{avg}} = 20, P_r = 0.06$ %) for the real number of adopters for PlayStation 3 and Xbox 360 over time, when using 100 000 consumer agents. All predictions lie within the shaded areas (i.e., "prediction range") ($n = 500$).



5 CONTRIBUTIONS AND IMPLICATIONS

5.1 Contributions

Our study offers a two-fold contribution. First, we provide a theoretical contribution to the literature on competition in platform-based markets. In the spirit of problematization (Alvesson & Sandberg, 2011) we challenged a domain specific assumption, namely, the assumption related to the size of the installed base and introduced a field-level assumption of selective attention to this domain. The development of such an alternative assumption ground enabled us to explain the observed "winner does not take all" outcome in the video game console market. According to the current understanding of competition in platform-based markets, the early entrant (Microsoft with its Xbox 360) should have had higher market penetration as it had a larger installed base initially, greater pool of complementary products, and lower initial price. However, it was the late entrant (Sony with its PlayStation 3) which ended up having higher market penetration. The extant literature on competition in platform-based markets fails to explain market outcomes such as the one in our study, as the previously studied empirical examples of platform-based markets have been mainly monopolist markets. However, as our study shows, in certain platform-based markets, multiple platforms share the market and, thus, we offer an important contribution in being able to explain why this happens. In this attempt, we incorporated a field-level assumption of selective attention into our study. We acknowledge that the assumption that humans are selectively attentive is a widely accepted one. For example, in the field of technological transition studies, the concept of frame resembles the concept of selective attention: in addition to evaluating the functional attributes of a technology, a potential adopter also evaluates the social connotation of the usage of a technology (Dijk et al., 2011; Dijk et al., 2016)[18]. However, to the best of our knowledge, our study is the first to incorporate demand-side dynamics on the micro-level and take into account selective attention of the consumers in the research on platform-based markets. As the adoption decisions of selectively attentive consumers are affected by the changes in complementary product quality in the market, it implies that the competitive advantage of a platform is partially tied to its ability to renew the pool of complementary products and ensure its quality. That is, if a late entrant is better in renewing the pool of complementary products and ensuring their quality relative to an early entrant, the former can obtain more adopters. In other words, not merely the size, but the change in size and quality of the pool of complementary products is a key factor affecting platform competitiveness.

Second, we contribute empirically to the research on platform competition. Our study is in line with Lee, Lee, & Lee (2006) and Afuah (2013) as we have developed an alternative assumption ground by stating

[18] We thank the reviewer for pointing out this adjacent field of research.

that consumers derive utility from their local network, that is, from the other consumers who interact with them. However, we also extend their work by testing the alternative assumptions ground, including both the assumptions of local bias and selective attention with empirical data. It has been shown that the given competitive outcome in the video game console market is not counterintuitive when we examine the platform competition in light of the developed assumptions. Further, we also tested alternative sets of theoretical assumptions and showed that they could not explain the market outcome. Therefore, our study provides strong empirical support for local bias, provided that the consumers are also selectively attentive. Local direct network effects restrict the early entrant from achieving the technological lock-in effect fast and enable for a late entrant to penetrate the market if it has the technological advantage. In other words, the superior perceived quality of a late-entrant can compensate for its disadvantage in terms of direct network effects, if and when the direct network effects are local.

In addition, although we do not have a true methodological contribution since we followed established procedures in empirical validation, agent-based modeling has not been utilized for prediction often and it still seems to remain ambiguous how to validate agent-based models empirically. Thus, we claim that our paper provides a valuable example and a benchmark on empirical validation of agent-based simulation models. We encourage agent-based modelers to pursue empirical validation more often as it adds to the generalizability of agent-based models, a typical problem that the critiques of agent-based modeling often refer to.

5.2 Managerial Implications

Our study suggests that the competitive advantage of a platform is partially reliant on complementary products. However, over time, a platform can face erosion of competitive advantage if the pool of complementary products is not renewed and quality is not ensured. This implies that platforms could employ both variance reduction mechanisms to improve the overall quality of complements (for example, see Boudreau, 2012; Wareham, Fox, & Cano Giner, 2014) and incentives for complementors to generate new complementary products and services. Thus, we claim that resilience and competitive survival may not be an outcome of generative ability; instead, input from the originator of the system (i.e., the platform) is probably needed to renew the pool of complementary products.

Second, as local direct network effects have been shown to be important for platform adoption, it is an interesting question whether the platform provider can control these. While this study cannot provide explicit answers on how to do this, it is clear that de-clustering the consumer network would benefit the early entrant.

In addition, our results imply that aggressive pricing did not help the early entrant platform to rapidly grow its installed base. However, it is analytically logical, given the formulation of utility indicators in this paper, that aggressive pricing might be an effective strategy. To put it another way, when the market is still in the making, a higher quality in complementary products enables a platform to attract more consumers even with a higher price. As shown in our study, because the late entrant (Sony) had the competitive advantage in terms of the complementarities, it enabled Sony to charge a significantly higher price than Microsoft initially, while still obtaining most adopters.

5.3 Limitations and future research directions

Our study has four main limitations that could also be addressed in the future studies. First, adoption decisions are modeled simplistically in our study. We modeled the decision to adopt in terms of selection of the platform, but we did not model adoption time decisions. Modeling adoption time decisions is important for predicting platform market sharing if many consumers do not consider all competing platforms as options when adopting a platform: then, it is important to know which consumers are biased in their platform decisions and when they make such decisions, due to the temporal nature of local direct network effects. In addition to making the model more general in terms of explaining platform market sharing, modeling adoption time decisions also enables analyzing which factors affect the diffusion of platforms as a category that is still relatively unexplored yet an important research topic.

Second, we did not endogenously model game developers' decisions about which platforms to develop for and at which quality, and similarly we assumed platform providers' strategic decisions (i.e., entry timing and pricing) from data as well. These choices enabled us to proceed with the empirical analysis—empirical analysis would have been highly challenging, had we modeled complementor and platform decisions, as they are likely to be affected by a multitude of unknown factors. Additional research is thus required to better understand the dynamics of complementary product markets and platform strategy. Further, methodological sophistication is required to deal with the endogeneity (e.g., arising from indirect network effects) so as to empirically analyze the decision making on both sides of a platform-based market and that of platform providers concurrently.

Third, we acknowledge that there may be additional factors affecting platform adoption, especially in different types of platform-based markets than the video game console markets, that we did not take into account in this study. One of such factors may be the compatibility of complementary products among different technology generations. If the complementary products were compatible with two consecutive generations of the same technology platform, this could promote brand loyalty (i.e., make a consumer having adopted the former generation to adopt the latter). However, in this particular case, PlayStation 3 and Xbox 360 were backward incompatible in practice, and hence brand loyalty should not have mattered for adoption. However, there may still be other unobserved reasons for brand loyalty. Further, we did not account for hardware quality differences between the platforms, as we had only anecdotal evidence of any quality differences, which we interpreted (based on the available data and literature) being unsubstantial in this particular empirical case. Nevertheless, our game quality measure should have controlled for any hardware quality differences, and future research could expand the analysis to account for platform hardware quality directly. Moreover, the technological development of both platforms and complementary products over time is evident in many platform-based markets and it most certainly affects platform adoption. However, as is typical to the video game consoles, the hardware for both PlayStation 3 and Xbox 360 were fixed during their lifetime (at least when it came to performance-related components). Thus, only the software could have developed technologically due to that the developers learned to exploit the console technology better over time. It is a good question whether this potential development in software quality was accounted for in the game reviews that were used as input to the alternative models. If not, then it should have been taken into account in the models, assuming technological quality does really affect game quality: however, this is not obvious when it comes to games, as they are played for entertainment, and the entertaining value of games is definitely not purely a function of their technological qualities like graphical glitz. All in all, the inclusion of additional factors affecting platform adoption would make the models more general.

Finally, although it appears that the small-world network model (Watts & Strogatz, 1998) used in this study can capture some of the most essential structural properties of real-life social networks, it is still a highly simplified model of reality. For example, it assumes that the consumer network is static, but in reality, social networks evolve over time. More realistic network models could be used to explain adoption in greater detail.

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