Demand Heterogeneity in Platform Markets:

Implications for Complementors

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Abstract

While two-sided platforms (e.g., video game consoles) depend on complements (e.g., games) for their success, the success of complements is also influenced by platform-level dynamics. Research suggests that greater platform adoption benefits complements by providing more potential users, but this assumes that platform adopters are homogeneous. We build on extensive research exploring the heterogeneity between early and late platform adopters to identify counterintuitive dynamics for complements. Complements launched early in a platform's lifecycle face an audience entirely of early platform adopters, whereas later-launching complements face a mixed audience of both early and late adopters, and we argue that differences in preferences and behavior between early and late adopters affect whether complements will succeed and which types will be most successful. We explore these dynamics in the context of the console video game industry using a unique dataset of 2,918 video games released in the United Kingdom from 2000 to 2007. We show that despite the increase in the potential user pool as the platform evolves, video games launched later in the platform lifecycle realize lower sales than those launched earlier. While increased competition explains part of this effect, we show substantial evidence consistent with our theory of preference differences between early and late adopters. This includes the finding that the negative effect is stronger for novel games and that the gap between popular and less popular complements widens as later adopters move into the platform, consistent with late adopters being risk averse and seeking to avoid purchasing mistakes.

Keywords: two-sided platforms, complementors, technology evolution, demand-side view, video games

"I understand the manufacturers don't want [new platforms] *too often because it's expensive, but it's important for the entire industry to have new consoles because it helps creativity. It's a lot less risky for us to create new IPs when we're in the beginning of a new generation."*

Yves Guillemot, CEO Ubisoft (as quoted in Morris 2012)

Introduction

Many goods and services are only valuable when they can be used in conjunction with complements. Two-sided platforms such as video game consoles and ride-sharing services are of limited value to consumers without compatible software and participating drivers. This interdependent relationship between platforms and complements leads to strong network externalities—consumers prefer platforms with more complements, and vice versa (Katz and Shapiro 1985). Platform sponsors such as Nintendo and Uber thus face challenges spurring growth on both sides of the platform (Parker and Van Alstyne 2005, Rochet and Tirole 2003), and the importance of complements for the success of platforms has led to significant research showing how platforms with the strongest complements are likely to succeed—effectively exploring how network externalities affect competition *between* platforms (Cennamo and Santalo 2013, Schilling 2002, Suarez 2004, Zhu and Iansiti 2012).

Recent research has also begun to explore how network externalities affect competition *within* platforms, or between producers of complementary goods (Boudreau 2012, Boudreau and Jeppesen 2015, Kapoor and Agarwal 2017, Yin et al. 2014).[2] The primary intuition is that the size of the platform's installed base—the number of consumers who have adopted the platform—positively relates to demand for complementary goods, as there is a larger potential market for complementors to pursue. This monotonic relationship between installed base size and complement demand rests on the assumption that platform adopters are homogenous. Previous studies, however, have found that platform adopters are in fact heterogeneous, and that user heterogeneity affects platform value in important ways. For example, Suarez (2005) and Lee et al. (2006) show that heterogeneous users with different connections value the

[2] Following previous work on platforms (e.g., Gawer and Cusumano 2014), we use the terms "complementor" and "producers of complementary products or services" interchangeably to denote organizations that sell products, or complements, that enhance the value of another firm's offering (Brandenburger and Nalebuff 1997).

benefits of network externalities differently (see also Afuah 2013). This suggests that a larger installed base may not always lead to better results for complements—a suggestion that we seek to explore here directly. This study's primary theoretical argument is that systematic differences between consumers who adopt the platform at different points in the platform's evolution importantly affect competition between complementors in ways that produce counterintuitive dynamics. This study therefore explores *how the evolution of a platform's user base from one dominated by early adopters to one dominated by late adopters affects performance outcomes for complementary products*.

By adopting a demand-side perspective on platform evolution (Adner 2004, Adner and Levinthal 2001, Adner and Snow 2010), we argue that complements launched early in a platform's lifecycle face an audience entirely of early platform adopters, whereas later-launching complements face a mixed audience of both early and late adopters. This suggests that whether complements will succeed, and which types of complements will be most successful, hinges in part on important underlying differences between early and late adopters of an innovation (Rogers 2003). Specifically, late adopters have a lower willingness-to-pay, are more risk averse, and search differently than early adopters (Cabral 1990, Geroski 2000, Taylor and Todd 1995). We argue that platform competition is therefore not only about more users always being better for complementors—the dilution of a pool of eager, high-spending early adopters with more conservative later adopters can negatively affect complements and will have varying effects on different types of complements such as those that are novel or innovative.

To analyze these dynamics, we use a unique dataset of 2,918 video games released in the United Kingdom from 2000 to 2007 on three competing platforms spanning an entire generation of video game consoles. The market for video games is often described as a canonical example of a two-sided platform: it includes platform sponsors (e.g., Nintendo) that create the technological infrastructure for video game publishers (e.g., Ubisoft) to commercialize content, and users who buy the consoles to enjoy compatible video games. Worldwide sales for the video game industry reached $100 billion in 2014, with over 70% of sales coming from video games and the remainder from hardware and accessories (Entertainment Software Association 2013, Gartner 2013). Video game consoles are a particularly fitting setting given their generational nature. Hardware systems have clearly demarcated beginnings and ends, and firms with competing consoles tend to launch relatively close to one another. This feature allows us to identify whether a video game launches on a platform composed of mostly early (vs. late) adopters and how this composition affects a game's sales (after controlling for installed base and product characteristics). The data further allow us to control for and rule out a number of alternative explanations, including the effect of competition between complements, the effect of the impending introduction of a next generation video game console, and unobserved heterogeneity at the game level.

Building our theory on the implications of differences between early and later platform adopters, we show an important and counterintuitive finding: despite the increase in the potential user pool as the platform evolves, video games launched later in the platform lifecycle realize lower unit sales than those launched earlier. Although competitive dynamics explain part of this effect, we show that the effect goes beyond competition alone. We suggest that these results show that demand-side shifts in the composition of the platform user base have an effect on the performance of complements even after controlling for network externalities and competitive crowding. Consistent with our theory on preference differences between early and late adopters, we also show that this negative performance effect is stronger for games based on novel intellectual property (which are seen as risky by late adopters that do not seek novelty) and that the gap between popular and less popular complements widens as more risk-averse late adopters move into the platform and seek to avoid purchasing mistakes.

This paper contributes in three primary areas. First, this paper extends our understanding of the intertwined relationship between platforms and complementary goods by showing that a larger installed base does not necessarily increase demand for complements when we consider the implications of demand heterogeneity among platform adopters (McIntyre and Srinivasan 2017). Thus, to the existing factors affecting complements of a larger installed base and more competitors (Boudreau 2012, Boudreau and Jeppesen 2015), we add the effect of different types of consumers. We add to previous work arguing that there is more to network externalities than installed base size (Afuah 2013, Lee et al. 2006, Suarez 2005) by emphasizing the importance of installed base composition. Our findings also add to research promoting an evolutionary perspective on platform competition (Gretz and Basuroy 2013, Gupta et al. 1999, Tiwana 2015, Tiwana et al. 2010) by looking at cross-platform evolutionary effects on the performance of complementary goods.

Second, by considering the impact of demand heterogeneity in platform based markets, this paper contributes to strategy and technology innovation studies that take a demand-side perspective (Priem 2007, Priem et al. 2013, Ye et al. 2012). We move beyond simply exploring demand heterogeneity within a single industry, instead suggesting that evolving demand conditions in one industry have important implications for firms' value creation strategies in related industries within the same (platform) ecosystem (Adner and Kapoor 2010, 2016). By going beyond noting that demand heterogeneity exists and pushing to articulate specific implications of those heterogeneities, we provide a theoretical foundation for future research to explore how fundamental differences between early and late adopters affect the viability of complementary products, technologies, and innovations.

Third, we contribute by suggesting strategic implications for complementors and platform sponsors. This study suggests how early adopters search broadly for complements and are willing to take risks, while later adopters gravitate towards complements with much greater certainty. This creates divergent complementor strategies based on the platform lifecycle: early in the platform's existence, firms should focus on throwing gravel by launching a wide variety of innovative products. Later in the platform's lifecycle, however, complementors are better off throwing rocks, investing their constrained resources in a limited set of familiar complements that largely extend the efforts made earlier in the platform's lifecycle. Given the increasing prominence of platform based markets, scholars have been interested in effective governance strategies for platform sponsors (Boudreau and Hagiu 2009, Wareham et al. 2014). Our findings contribute by identifying specific types of complements that platform sponsors should encourage (and discourage) entering at different stages in the platform lifecycle.

Theory Development and Hypotheses

In two-sided platforms, the availability of complementary goods affects the success of the platform. For example, operating systems are only valuable when they are used in conjunction with compatible software applications. This influence of complements on platforms inspired researchers to focus on how changes on the complements side affect demand on the platform side. The central argument revolves around network externalities: an increase in the number of complements supporting a platform results in increased adoption of the platform. More compatible applications will drive up demand for operating systems, and an increase in merchants accepting a credit card will boost the card usage. This notion of network externalities was first explored formally by Katz and Shapiro (1985, 1986, 1994) and later tested empirically by researchers in economics (Clements and Ohashi 2005, Nair et al. 2004), marketing (Stremersch et al. 2007), and management (Schilling 2002).

This study focuses on the reverse dynamic: how demand for complements is affected by dynamics on the platform side. Research addressing demand for complementary goods is still sparse and has mostly focused on the role of network externalities and competition (Boudreau 2012, Boudreau and Jeppesen 2015) or on the effects of product characteristics (e.g., Eckhardt 2016, Kapoor and Agarwal 2017, Yin et al. 2014). Our work builds on this emergent but growing body of literature by investigating how changes in the composition of the installed base affect demand for complementary goods. We begin our theory development by discussing how the two differentiating dynamics of two-sided platforms (i.e., network externalities and competition) affect demand for complements. We then articulate how demand-side heterogeneity among platform adopters may additionally affect the sales performance of complements. We do this by first identifying a series of preferences and behaviors distinguishing early from late adopters, and then describing how those factors influence complement performance.

A Typical Model of Complement Performance

Research has explored two platform-specific factors that are central to understanding the performance of a given complementary good: the size of the installed base of the platform and the competitiveness of the complement space. We discuss these briefly below.

First, complements intuitively draw their sales from a potential user pool composed of the installed base of the platform. The decision to purchase a complementary good is a contingent innovation decision: only after having adopted a platform will a consumer consider purchasing complements for said platform (Bayus 1987, Rogers 2003). Compatible software applications can only be meaningfully used by consumers who also adopted the operating system, and the number of visitors to a shopping mall determines stores' maximum clientele. This suggests that complements launched on platforms with a larger (vs. smaller) base of users are likely to generate higher levels of sales, all else being equal. The importance of these cross-platform network externalities for complements' sales performance has been explored empirically in applications for Personal Digital Assistants (PDAs; Eckhardt 2016) and online multiplayer video game platforms (Boudreau and Jeppesen 2015). Thus, we would expect the number of potential consumers (i.e., adopters of a given platform) to play a significant role in driving the performance of that complement.

Second, research on platforms has highlighted the importance of same-side network externalities: the effects of adding more complements to a platform. Increases in the installed base of a platform not only expand complementors' potential market size but also trigger additional entry by new complement providers. This incentive for entry can cause a negative crowding effect when the rate at which complements enter the platform outweighs new platform adoption by users. Such over-entry may hamper complements' sales performance when too many competitors are active on the platform, vying for the same user base. It should be noted that the net effect of same-side network externalities on complements (i.e., triggering increases in the installed base and boosting platform entry by complements) is not straightforward and may lead to either positive or negative outcomes depending on the characteristics of the market (Parker and Van Alstyne 2005). Looking at applications for PDA devices and online multiplayer game platforms, Boudreau has explored the workings of this dynamic and found support for the competitive crowding effect (Boudreau 2012, Boudreau and Jeppesen 2015).

Prior research offers these two platform-specific factors affecting complements' performance: installed base size (positive effect) and competition among complements (mostly negative effect). Below we explore an additional factor that offers a counterintuitive theory about complement performance as the platform evolves: underlying heterogeneity in the platform user base, specifically in terms of different preferences for consumers who adopt a given platform early in the platform's lifecycle versus those who adopt it later. We explore these differences—and implications for complements—below.

Effects of Early and Late Platform Adopters on Complements

Research on the diffusion of innovations has long asserted that key differences exist between the early and later adopters of an innovation. We recognize that adopter types are continuous, but for simplicity we distinguish between two groups—early adopters and late adopters.[3] While Rogers (2003) outlines many differences between early and late adopters, including age and gender, here we focus on four factors that have particular implications for our theory development: willingness-to-pay, risk aversion, preferences for novelty, and search processes. We cannot measure these factors directly, but we discuss below how they have been shown to differ systematically between early and late adopters, providing an important window into consumer preferences that are typically difficult to assess. And while there may be alternative explanations for the empirical relationships suggested in our hypotheses—explanations related to user base size, complementor competition, platform generation transitions, and complement heterogeneity—we discuss and empirically address these issues in our analysis.

First, early adopters of an innovation (including a platform) will be more willing to spend time and money on the platform and its complements than later adopters. The underlying logic is that early adopters make adoption decisions without knowing whether the platform will emerge as the dominant design, often paying an even higher price for the platform than late adopters (Schilling 1998). Cabral (1990) offers a model of platform adoption that concludes that early adopters must have a higher willingness-to-pay for the technology since they adopt without the benefits of certainty. The rate of adoption by subsequent users (both consumers and producers of complementary goods) strongly affects

[3] Diffusion processes follow a normal distribution where *innovativeness*—"the degree to which an individual … is relatively earlier in adopting new ideas than other members of a social system"—is partitioned into standard deviations from the average adoption time (Rogers 2003, p. 208). Similar to the platform lifecycle, cumulative adoption follows an S-shaped curve where the mean denotes the separation between early and late adopters. Rogers identifies five adopter categories: innovators (2.5% of all adopters), early adopters (13.5%), early majority (34%), late majority (34%), and laggards (16%). These categories are exhaustive in that they include all adopters of a given innovation but exclude non-adopters.

the value of a platform (Brynjolfsson and Kemerer 1996, Gandal 1994), but it is often unknown to early adopters which platform will eventually enjoy the highest adoption rate (Katz and Shapiro 1994). Karshenas and Stoneman (1993) build on this perspective to suggest a "rank effect" process, whereby the potential adopter with the highest preference adopts first, followed by adopters who have lower valuations. Empirically, Kretschmer and Grajek (2009) show this phenomenon in the mobile network industry, where early adopters of mobile technologies use the technology much more intensively than later adopters (see also Golder and Tellis 2004). In general, prior research has established that early adopters of an innovation tend to value the innovation more highly than later adopters.

This difference in willingness-to-pay between early and late adopters is especially relevant for the suppliers of complementary goods, as platform adopters typically purchase the platform not for itself but for the ability to use complementary goods (Schilling 2002). In contingent innovation decisions, adopters' predispositions towards the prior innovation generally also apply to subsequent innovations (Rogers 2003, Shih and Venkatesh 2004). This, combined with research showing that preferences tend to be relatively stable for a given person over time (Andersen et al. 2008, Harrison et al. 2005), suggests that it is reasonable to assume factors distinguishing early adopters of the platform from late adopters also characterize their interaction with complements on the platform. We therefore expect the higher valuation of the platform to mean that early adopters are more willing to spend money and time on complements than later adopters. The result is that as the installed base of a given platform shifts from early adopters with higher valuations towards later adopters with lower valuations, demand for individual complements will actually decline.[4] This effect, of course, presumes the ability to control for the two known factors that affect complement sales (size of the installed base and density of competition). More importantly, though, this consideration of the *composition* of the installed base, and not just its size, produces a theoretical expectation that runs contrary to the typical intuition about complement performance, which presumes

[4] Technically, for complement demand to decline as adopters have lower willingness-to-pay, the pricing of the product would have to increase, stay constant, or decline at a rate slower than the decline in willingness-to-pay. Empirically, we can control for multiple ways that pricing may affect adoption decisions. But from a theoretical perspective, this is an important boundary condition of the theory.

that more platform users is always better. We thus argue the following:

> *Hypothesis 1. As a platform's user base shifts towards more late (versus early) adopters, the number of units sold of any individual complement on the platform will decrease.*

This hypothesis suggests that sales will decline as the user base shifts, and this may occur through two processes: all complements could suffer equally, or some types of complements could suffer disproportionally relative to others. Consistent with our emphasis on heterogeneity in consumer preferences, we suggest that this demand heterogeneity will affect different types of complements differently. Specifically, early platform adopters differ from late adopters in important ways beyond willingness-to-pay that have implications for complement providers. To develop testable predictions about heterogeneity in complementor performance, we focus on three strongly intertwined differences between early and later platform adopters: risk aversion, preferences for novelty, and search processes.

First, early adopters are typically less risk averse than late adopters. Geroski's (2000) review of the innovation diffusion literature notes that a number of studies have explored differences in risk attitudes between early and late adopters, and used these differences to explain the adoption curve of new technologies: early adopters are willing to adopt a new, uncertain, and potentially unsuccessful innovation before others in part because they have a greater tolerance for risk. Leonard-Barton (1985) notes that this aversion to uncertainty may be due to late adopters often having less disposable income than early adopters and thus being at greater risk with any given innovation decision.

Second, early adopters are more likely to value and seek out novelty than late adopters. In her classic article, Hirschman (1980) articulates how novelty seeking is about the desire to accumulate new information about options and to have new experiences. She suggests that some consumers have a strong and persistent preference for novelty and variety, viewing novelty seeking as a persistent, internal force that encourages new experiences. Similarly, Kahn (1995) notes that much of the existing literature has identified consumers with a strong preference for novelty for the sake of novelty itself. Related research has explored how preference for novelty is linked to adoption timing. Ram and Jung (1994) suggest that "usage needs … tend to vary across consumers who adopt the product at different stages of the lifecycle"

(p. 58) and empirically link novelty seeking with early adoption timing, or use innovativeness (see also Venkatesh and Vitalari 1986). Vishwanath (2005) explores preferences and adoption timing across a number of technology hardware products and finds that tolerance for novelty is tied to adoption timing, with early adopters being more tolerant of novelty, while Chau and Hui (1998) show a similar relationship in computer operating systems. This harkens back to Rogers' (2003) statement that early adopters need to handle ambiguity well, as novelty has been defined a key aspect of ambiguity (Budner 1962). In addition, Hirschman's (1980) initial suggestion was that novelty seeking and use innovativeness are inherently complementary concepts. This preference for and tolerance of novelty is likely what leads these consumers to be early adopters of an innovation in the first place: they derive utility from exploring and experiencing a truly new innovation.

Third, later adopters search for and select between competing innovations differently from early adopters. These differences derive from risk preferences and a lack of technological sophistication inherent in the unwillingness to explore novel options. Combined with the fact that better information is available about the platform and its complements later in the platform lifecycle, late adopters are more able to rely on a few reliable external signals about which complements to purchase (Boatwright et al. 2008, Zeithaml 1988). In some contexts, these signals may be familiar brands (Eggers et al. 2016); in other contexts, this difference in search behavior may be linked to reliance on expert opinions in making choices (Wijnberg and Gemser 2000). Thus, later adopters are more likely to exhibit herding behavior towards a limited, safe set of products.

These three factors that systematically define early versus late adopters—risk, novelty, and search—generate two important implications for complementors in platform settings. First, novel complements are likely to struggle as the platform's user base is composed of more and more late platform adopters that are risk averse, do not value novelty, and rely on familiar signals to make purchasing decisions. Similar to newly launched platforms, novel complements are shrouded by uncertainty, thus imposing valuation ambiguities. The higher risk around novel complements makes them appeal more to early adopters than late adopters. Our second hypothesis therefore is as follows:

Hypothesis 2. As a platform's user base shifts towards more late (versus early) adopters, the number of units sold for novel complements on the platform will decline at a faster rate than for non-novel complements.

In addition, differences in risk preferences and search behavior will likely affect the relative demand for the most and the least popular complements on the platform. That there is a disparity between popular ("superstar") complements and less popular ("flop") complements is obvious. What is important is that the pool of early adopters is more likely to search broadly across the full range of complements and should be less concerned about the risks of adopting a complement that they end up not liking. Thus, the gap between the best- and worst-performing complements on the market will increase as the potential adopter pool shifts from risk- and novelty-seeking early adopters to risk-averse later adopters making relatively homogenous adoption decisions.[5] Our third hypothesis therefore is as follows:

Hypothesis 3. As a platform's user base shifts towards more late (versus early) adopters, the unit sales disparity between more popular and less popular complements on the platform will increase.

In all, our core theory is that the composition of the installed base matters for complement performance. Fundamental differences between early and late platform adopters lead to an environment where complementors sell less—especially risky complements such as those perceived as novel or as likely to be flops—as the user base shifts towards more late adopters.

Research Setting: Console Video Games in the UK (2000-2007)

We test our theory with data on sixth generation console video games in the United Kingdom, one of the three largest markets for video games globally. The video game industry is a fitting setting for our tests for three reasons. First, game consoles are a platform market. The industry includes platform sponsors (e.g., Nintendo) that create the infrastructure for video game publishers (e.g., Ubisoft) to commercialize content, and users who buy the consoles to enjoy compatible games. Users are generally attracted to the

[5] Note that increasing sales disparity could occur through two different processes: the negative impact of a shift towards later adopters could disproportionately affect the best complements, or it could affect the lowest performing complements. Given the concerns of late adopters about making mistaken purchase decisions, it would make sense that the negative effect might most significantly affect the lowest performing complements, but we explore this suggestion empirically.

platform with the highest number of games available, while publishers prefer the platform with the largest user base. As with most platforms, console sponsors generate revenues through console sales to consumers and royalty payments from publishers.[6] Second, game consoles have clearly defined beginnings and ends. Given the substantial financial investments made by platform sponsors, next generation game consoles are typically released only every five to eight years, providing substantial differences between the early and late periods in a platform's lifecycle. Third, there is a constant supply of video games throughout platforms' lifecycles, and variation in the *types* of games and their market performance (see Figure 1, discussed below). Our focus on the UK provides a benefit for identification: given that (1) game development occurs globally with hotbeds in the US, Japan, and UK (Izushi and Aoyama 2006, Johns 2006);[7] (2) games are often launched simultaneously in these markets; and (3) the exact demand for video games and game consoles varies across countries, we are less concerned about potential biases driven by game publishers strategically making entry decisions to match patterns in platform demand or platform market shares in the UK.

We focus on sixth generation video games as this is the most recent generation for which data on a completed platform lifecycle was available at the time of data collection. Sixth generation platforms include Sony's PlayStation 2 (PS2), Microsoft's Xbox, and Nintendo's GameCube. The PS2 was first to enter the UK market, in November 2000, followed by Xbox and GameCube in March and May of 2002, respectively. PS2 quickly became the dominant player, with a UK market share of 74% (and an installed base of 9.08m) compared with Xbox's 17% market share (installed base of 2.14m), and GameCube's 9% market share (installed base of 1.05m). The PS2 was also the console most supported by game publishers: 1,775 of the 2,918 games in our sample were released on PS2, with the remainder on Xbox (738 games) and GameCube (405 games). Eventually, sixth generation consoles were replaced by technologically

[6] Platform sponsors also engage in some video game production. In our sample, less than 9% of the games are published by one of the platform sponsors. We control for this by including firm fixed effects in our estimations.
[7] In our sample, 47% of games are produced by game publishers located in the US, 20% are produced by game publishers located in Japan, and 19% are produced by publishers in the UK. More than 70% of the games in our sample were also released in the US, and approximately 30% were released in Japan.

superior seventh generation machines. The seventh generation was initiated in the UK by Microsoft's Xbox 360, in November 2005, followed by Nintendo's Wii, in December 2006, and Sony's PS3, in March 2007. Table 1 provides an overview of descriptive statistics per console, and Online Appendix Figure A1 graphically depicts sixth and seventh generation consoles' lifecycles from 2000 to 2007.

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Some of the most popular video game franchises in our sample include *Grand Theft Auto*, *FIFA*, *Need for Speed*, *Halo*, and *Super Mario*. *Grand Theft Auto: San Andreas,* released in 2004 on PS2, was the bestselling video game in the UK, with 2.3 million units sold. On average, video games attained the highest sales performance on PS2 (65,810 units per game), followed by Xbox (28,077 units per game), and GameCube (18,237 units per game). This shows that video games' unit sales are generally correlated with their platform's installed bases. Nevertheless, novel video games released during our study timeframe display a rich variation in sales performance. Nintendo, for example, successfully launched *Pikmin*, a video game based on a new intellectual property, early in the GameCube's lifecycle, in 2002. The real-time strategy game received rave expert evaluations and sold nearly 70,000 units. By contrast, when THQ released *Psychonauts*, another novel video game based on new intellectual property that received rave expert scores, towards the end of the PS2 lifecycle, in 2006, it sold fewer than 12,000 units. The contrast between these examples is even more marked when taking into account GameCube's significantly lower installed base in comparison to PS2. These data points lend anecdotal support to our conjecture that complement sales are not solely correlated with the size of the installed base.

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Figure 1 provides descriptive statistics on platform entry and median unit sales by game type plotted against the platform's diffusion rate. The figure shows that (1) there is sufficient platform entry from both types of video games throughout the platform's lifecycle, and (2) median sales of both types of video games decline as the platform becomes more diffused, but (3) sales for games based on new intellectual property (IP) decline at a faster rate than sales for games based on existing IP. The trends in the raw data are thus consistent with our hypotheses, which is encouraging. It is briefly worth noting the dramatic upswing in game launches very late in the platform's lifecycle. In part this is driven by the fact that platform diffusion slows, so the last deciles represent a relatively longer period. Even so, though, we find that game developers launch games at a very fast pace towards the end of the platform's lifecycle, something that we address in more detail in the Discussion section.

Data Sources and Structure

We built a novel dataset of the population of sixth generation console video games released in the UK from 2000 to 2007 (2,918 games). Data on all three platforms were provided by one of the platform sponsors include annual platform sales, total platform-specific game sales (units and revenue), game and platform release dates, game genre, and game publisher. The sell-through data were collected in the last week of 2011 and include over 90% of all (i.e., brick-and-mortar and online) transactions in the UK. Game quality was collected from the expert review aggregator Metacritic.com. Data on video game novelty were hand-collected by three research assistants. Our dataset is organized at the game-platform level, with a single observation per game for each platform on which it was released.

Dependent Variable

Complement sales is operationalized as the video game's platform-specific lifetime *unit sales* (using sales revenue produces similar results). Though we do not have time series sales data for most games in our sample, we are not concerned that using a single lifetime sales measure obfuscates our results. Video games have very short lifecycles, with most releases generating the bulk of their sales within the first few months. Our data display trends similar to Nair (2007): 80% of video games' lifetime unit sales are generated in the first year from launch (see Figure 2). These trends are consistent across platforms and across video games' release dates. There is also no concern about right-censoring biases, as we collected our data in the last week of 2011, four years after the last game in our sample was released. Such concerns are further alleviated by the notion that our primary interest involves differences between novel and non-novel games, and that all games released at the same time would be subject to the same (if any) biases. So even though games launched later in the platform's lifecycle would appear to have less time on the market to accumulate sales, since the majority of sales occur within one year and our data capture four years after the last game was released, we do not believe this affects our results.

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We focus on game-platform-level unit sales because many games multi-home, meaning that they are launched on multiple platforms, typically at the same time (Corts and Lederman 2009; Landsman and Stremersch 2011). Given that our theory is at the platform level and that rival platforms will be at different diffusion rates at the same point in time, using platform-specific game sales allows us to capture different effects by platform. In some of our models discussed below, we exploit the subsample of multi-homing video games to employ a game fixed-effects regression that allows us to rule out any unobserved heterogeneity at the game level, instead focusing on the variance in diffusion rates at the platform level. As games' *unit sales* are highly skewed, we log-transform our dependent variable.

Independent Variables

Our theory focuses on the extent to which a given game is launched to an audience composed primarily of early versus later adopters of the platform, as the fundamental differences in the needs and wants of early versus late adopters create important challenges for firms. The empirical challenge is that we cannot measure the exact composition of the installed base or adopter pool for any given game. This is because we do not possess individual-level data, as such data is not systematically collected in the video game industry. As a result, our empirical approach is to identify two time-varying constructs that we believe are strongly correlated with the composition of the potential pool of game adopters at the time of the game's launch: the extent of platform diffusion and the installed base of the platform's next generation successor.

By definition, a game launched very early in a platform's lifecycle will be facing a pool of potential adopters composed only of early platform adopters. In contrast, a game launched towards the tail-end of a platform's lifecycle will be launching to a mixed pool of early and late platform adopters. Rogers (2003) splits adopters into five categories and provides average percentages of the total adopter pool in each category. Note, however, that these adopter categories are a conceptual tool and that the underlying dimensions distinguishing early adopters from late adopters are, in fact, continuous. We therefore sought to identify a continuous variable that would track the evolution of the platform's user base from 100% early adopters at the start to a user base more heavily weighted towards later adopters. We proxy for the changing composition in a game console's user base with a variable that captures each platform's diffusion at the time of a focal game's release:

$$Platform\ diffusion_{jt} = \frac{Installed\ base_{jt}}{Installed\ base_{j}}$$

The numerator $Installed\ base_{jt}$ measures platform j's installed base at time t of the focal game's release, and the denominator $Installed\ base_{j}$ measures the installed base of platform j at the end of its lifecycle.[8] The resulting variable ranges from zero to one and allows for a straightforward interpretation of the effect of a platform's diffusion on game sales within and across platforms.

Additionally, we build on prior research to argue that the introduction of next generation platforms affects the balance between early and late adopters on a current generation platform. The idea of a next generation technology competing with and displacing the current technology is a common phenomenon in video games, mobile phones, and many other technological innovations (Adner and Kapoor 2016, Adner and Snow 2010). Research in PDAs (Kim and Srinivasan 2009) and smartphones (Huh and Kim 2008) suggests that stability of adopter preferences leads the early adopters of one generation to be early adopters of the next generation. This means that, as the next generation platform gains traction, the share of early-adopter-type consumers still active in the existing generation platform will decline as these consumers move to the new platform. Such migration further skews the potential game adopter pool towards later adopters of the platform. Our second proxy for the changing composition of the platform's user base therefore is the size of the *next generation installed base (IB)* at the time of the focal game's release. We link each platform to its same-brand successor (e.g., Sony PS3 for PS2) and count the number of next generation consoles sold up to the time of the focal game's release. There are

[8] Following previous studies, we denote the end of a console's life to occur when monthly platform sales fall below a certain threshold, or when we observe a month without any game introductions (Binken and Stremersch 2009, Cennamo and Santalo 2013, Landsman and Stremersch 2011). In their studies of US game consoles in the same timeframe, Binken and Stremersch (2009) and Landsman and Stremersch (2011) use a monthly threshold of 5,000 consoles sold. Since the market analysis firm IDG (2011) estimates that the UK installed bases for sixth-generation game consoles are roughly 20% of the corresponding US installed bases, we use a threshold of 1,000 units.

nine months in our study sample where PS2 co-existed alongside PS3, 13 months where Xbox co-existed alongside Xbox 360, and zero months in which the GameCube co-existed alongside Nintendo's Wii. We log-transform *next generation IB* to account for its skewness. We use these two measures capturing platform installed base composition—*platform diffusion* and *next generation IB*—to test H1.

Hypothesis 2 concerns differences between novel and non-novel complements. Novel video games are those games that are based on an entirely new, or original, IP. Video game publishers see creating new IPs as the fundamental innovation activity in their industry: "Like other entertainment companies, our business is significantly based on the creation, acquisition, exploitation and protection of intellectual property."[9] Therefore, and following Tschang (2007), we operationalize novel games as those that are based on original IP rather than existing video game properties (i.e., sequels, prequels, or spin-offs), sports licenses, or non-video-game media tie-ins (i.e., movies, TV series, and books). *New IP* is a binary variable that takes the value of 1 if a video game is based on a new IP and 0 otherwise. Two graduate students and an industry expert consulted games' box covers and other online sources to understand whether the video game was based on a new IP. In our sample, 29% of all video games are based on new IP. This percentage corresponds with generally accepted statistics of non-imitative or truly new innovations in a market (Kleinschmidt and Cooper 1991). Figure 1 displays the distribution of video game introductions by type against the diffusion of the platform. The figure illustrates that although the rate of new IP introductions drops from 42% early in the platform lifecycle to 20% at the end of the platform lifecycle, there exists sufficient variation in the number of new IP games entering the platform as it evolves and becomes fully diffused.

Hypothesis 3 concerns the gap in sales performance between popular, or "star," and less popular, or "flop," complements. We investigate this hypothesis by assessing whether *platform diffusion* and *next generation IB* vary in their influence on games' unit sales at different points in the sales distribution. Thus, we do not need to introduce any new variables to test H3.

[9] Electronic Arts 2010 Annual Report: http://investor.ea.com/ar2010/PDF/electronic_arts-2010_0087.pdf (last accessed January 2017).

Control Variables

The two primary factors that we need to control for based on the motivation for our study are the two platform-level factors already shown to influence the performance of platform complements—the number of available consumers who may purchase the complement, and the level of competition among complementors supporting the platform. We control for these factors to rule out specific alternative explanations for the observed impact of platform-side dynamics that form the basis of our theory. The most intuitive way to measure the size of the potential adopter pool is through a measure of installed base (the cumulative number of users who have already adopted the platform). The primary concern is that the cumulative installed base may overstate the size of the indirect network effects (Nair et al. 2004). The underlying logic is that users become inactive after a certain period since buying the platform. While our results are robust to using the entire platform installed base (see Online Appendix), we instead follow past work on complement sales in networked markets and include a measure of recent platform sales, as opposed to total platform sales (Eckhardt 2016). Through interviews with industry executives we learned that users purchase the bulk of their games in the year following their purchase of the platform. *Platform sales* therefore measures the number of consoles sold over a rolling window of one year prior to the launch of the focal game. We introduce a one month lag to reduce concerns about reverse causality. Also, due to the variable's skewness we take the log-transformation. Since the negative effects of competitive crowding are strongest when entry occurs by rival complements in the same category as the focal complement (Boudreau 2012), we control for same-side network effects through a measure of *genre competition*. *Genre competition* counts the number of same-genre video games entering the platform in month *t* of a focal game's release. Here too, we address concerns of reverse causality by introducing a one month lag (unlagged variables produce similar results).

In selecting additional controls we focused on important product characteristics shown to influence video games' performance. First, we control for video games' quality via expert review scores from Metacritic.com. Metacritic tracks over 300 online and offline publications that publish video game reviews, from which it aggregates and weighs an average 'Metascore' at the game-platform level.

Metascores are highly regarded in the industry and are often used as a yardstick of video games' quality. Metascores range from 0 to 100; 100 indicates a perfect score. Metacritic uses these continuous variables to create a colored grading scheme that we adopt to create a categorical variable indicating whether the game's quality is "good" (75 or higher, n = 787), "average" (50–75, n = 1,139), "bad" (< 50, n = 146), or missing (n = 846; base category). We choose to use this categorical measure of quality as there exist strong threshold effects, with variance in scores above or below the thresholds having minimal impact on sales. Results using a continuous measure of game quality are in the Online Appendix.

Second, we control for video games' distribution patterns by including a dummy variable that indicates whether a game is released exclusively for one console (vs. multi-homing). While *platform exclusive* games are known to boost demand for platforms (Corts and Lederman 2009; Landsman and Stremersch 2011), it is unclear how exclusivity affects sales of the game itself. On one hand, exclusive content can be tailored to the exact technical specifications of the platform, which can result in higher quality through better fit, leading to increased sales performance. On the other hand, exclusivity may be negatively correlated with publishers' development and marketing budgets, and a narrow release may reduce consumers' overall awareness of a game. While we are agnostic about the direction of the effect of exclusivity on sales, we feel it is important to control for this factor.

Last, to control for systematic variation in consumer preferences across game genres, we include 14 genre dummies.[10] Additionally, as the market for video games is characterized by strong seasonality since many games are released in the weeks leading up to Christmas, we include 11 month-of-release dummies, excluding January as base. We further control for heterogeneous resources and capabilities (e.g., game engines, marketing capabilities) at the firm level by including 71 publisher dummies. Finally, time-invariant differences at the platform may also structurally affect game sales; therefore, we include two platform fixed effects excluding PS2 as the base category. Our final sample for estimation includes

[10] There are 15 genres in the dataset: action (base), fighting, graphic-adventure, music, non-game, platform, puzzle, racing, real game, role playing game, shooter, simulation, skateboarding, sports, and war.

2,918 video games on three platforms released across 191 console-months.[11]

Analytical Approach

Our empirical analyses rely on various linear regression models that take the following form:

$$ln(Unit\ sales)_{ij} = \beta X_{ij} + \beta_0 + \varepsilon$$

where the log of game $_i$'s cumulative unit sales on platform $_j$ is regressed on βX_{ij}, a vector of covariates including *platform diffusion*, *ln(Next generation IB)*, *new IP*, their interactions, and the control variables discussed earlier. The models further include a constant β_0 and an error term ε. Hypotheses 1 and 2 are tested primarily by relying on OLS regressions, although we also use propensity score matching (PSM) techniques to help rule out concerns of endogeneity (discussed in more detail below).

To test Hypothesis 3, we use weighted least absolute deviation estimators, or quantile regressions (Koenker and Bassett 1978). Quantile regressions are apt estimators when the researcher is interested in how covariates affect various points in the distribution of the dependent variable. Our approach aligns with recent studies using quantile regressions to estimate different levels of performance in innovation contests (Boudreau, Lacetera and Lakhani 2011) and DVD rental rates (Elberse and Oberholzer-Gee 2007). By jointly estimating and comparing coefficients for observations in the lower quantiles and higher quantiles of the dependent variable, we can draw inferences about the effects of *platform diffusion* and *next generation IB* on the sales disparity between star and flop video games. We report outcomes to $Quant_\tau$, where $\tau = 10$ estimates less popular games and $\tau = 90$ estimates more popular video games.[12] We then assess the differences between the coefficients by estimating interquantile-range regressions.

Baseline Results

We conduct three empirical tests to identify the effect of the console's changing user base on games' unit

[11] High collinearity between the progression of time and *platform diffusion* prevents us from controlling for time trends. Additionally, since our dependent variable is the game's cumulative unit sales, it is not productive to control for games' prices (i.e., producers will strategically adjust their prices to influence demand during the game's lifecycle). This is further reinforced by the fact that video games are typically launched at recommended retail prices imposed by the platform owner (Nair 2007). We address these potential limitations in the Online Appendix.

[12] The main results reported for the interquantile-range regressions are robust to using alternative quantiles (e.g., τ80–τ20; τ75–τ25) for popular and less popular games.

sales. First, we use OLS regressions on our full sample to test H1 (about the main effects of *platform diffusion* and *next generation IB*) and H2 (about the differential effects for *new IP* and *existing IP*). These provide our baseline results. Second, to address concerns of unobserved heterogeneity at the game level, we exploit the fact that many games multi-home, which allows us to use models with game-level fixed effects that eliminate concerns about missing variables or the strategic timing of product launch. Third, we take a different approach to controlling for differences between games by performing a splined-sample matching regression where we link each *new IP* game to its closest *existing IP* game within every decile of the *platform diffusion* variable. Collectively, we believe that these tests provide good identification of the effects that *platform diffusion* and *next generation IB* have on games' *unit sales*.

Testing Hypotheses 1 and 2

Table 2 lists descriptive statistics and pairwise correlations. Table 3 shows the results of the baseline OLS regressions that test H1 and H2 by estimating the full sample. Model 1 includes quality, genre, publisher, platform, and calendar-month-of-release dummies, Model 2 adds control variables, and Model 3 and 4 test H1 by adding *platform diffusion* and *next generation IB,* respectively. Models 5 and 6 test H2 by adding the interactions between *platform diffusion* and *new IP* and *next generation IB* and *new IP*, respectively. Model 7 includes all covariates and explains 52% of the variation in the dependent variable.

--- INSERT TABLES 2 AND 3 HERE ---

We focus on Model 3 for the main effect of *platform diffusion* on game sales. Consistent with our first hypothesis, we find that as platforms become more diffused, games' unit sales decrease. Games that are released on fully diffused platforms attain 19% lower unit sales than games released on newly launched platforms ($p < 0.01$). Support for H1 is further corroborated in Model 4, which adds *next generation IB* as an alternative measure to reflect the changing composition of the platform's installed base. In line with H1, we find that a 10% increase in the installed base of a next generation platform correlates with a 2.26% decrease in game sales ($p < 0.01$). Overall, these results are consistent with the intuition that platform complements perform comparatively worse when launching to a mixed pool of early and late platform adopters than when they launch only to early platform adopters.

Our second hypothesis concerned the differential effect that the changing installed base composition has on novel versus non-novel complements. While we do not offer any theory about the main effect of *new IP*, we find that *new IP* games have 31% lower unit sales than *existing IP* games ($p < 0.01$; based on Model 3 results). This finding is consistent with the notion that innovation tends to produce lower payoffs on average (March 1991). We test H2 in Model 5 by interacting *new IP* with *platform diffusion*, and in Model 6 by interacting *new IP* with *next generation IB*. In Model 5, the interaction term with *platform diffusion* is negative and significant ($p < 0.01$). When platforms are fully diffused, *new IP* games have 26% lower unit sales than at the beginning of the platform lifecycle. We also note that the main effect of *platform diffusion* becomes smaller after including the interaction term (−9.52%; $p < 0.01$), indicating that *new IP* games are disproportionally driving the negative effect of *platform diffusion* on sales, consistent with our theory. Results are also consistent with our alternative measure of installed base composition. In Model 6 we find that the effect of *new IP* is more pronounced for games launched after the entry of the next generation platform: a 10% increase in *next generation IB* correlates with a 4.38% decrease in *new IP* game sales ($p < 0.01$). Here, too, we find that the main effect of *next generation IB* becomes smaller (−1.89%; $p < 0.01$), again suggesting that *new IP* games are disproportionally driving the negative effect of *next generation IB* on games' unit sales. Overall, these results are strongly consistent with H2, suggesting that the negative effects of the shift towards later platform adopters would be more pronounced for novel complements than for non-novel complements.

Our control variables all perform as expected. Lending support to the notion of cross-platform network externalities, we find that game sales positively react to increases in *platform sales* ($p < 0.01$; based on Model 7 results). A 10% increase in platform sales correlates with a 1.15% increase in game sales. We also find support for the competitive crowding hypothesis (Boudreau 2012, Boudreau and Jeppesen 2015), as games realize lower unit sales when there are more same-genre games entering the platform ($p < 0.01$). One additional same-genre game entering the platform reduces average game sales by 3%. We further find that *platform exclusive* games have, on average, 19% lower unit sales than multi-homing games ($p < 0.01$), and that games with high Metascores have 72% higher unit sales than games with average Metascores ($p < 0.01$), 140% higher unit sales than games with low Metascores ($p < 0.01$), and 116% higher unit sales than games with missing scores on Metacritic ($p < 0.01$).

Testing Hypothesis 3

We test Hypothesis 3, which posits that the shifting composition of the platform user base widens the gap in sales between more and less popular complements, in two distinct steps. First, we jointly estimate the effect of *platform diffusion* and *next generation IB* at two points in the distribution of the dependent variable using simultaneous quantile regressions: the 10th quantile for less popular, or "flop" games (τ = 10), and the 90th quantile for more popular, or "star" games (τ = 90). Next, we estimate the difference between the coefficients for these covariates through an interquantile-range regression to assess whether higher and lower selling games are affected differently by our user base proxies. In Models 1 and 2 of Table 4, we estimate the effects of our covariates on flop games and star games, respectively. We then estimate the differences between these coefficients and the extent that they are significant in Model 3. Robust standard errors are estimated using the bootstrapping method based on 1,000 draws.

--- INSERT TABLE 4 HERE ---

The results reported in Table 4 are consistent with H3. We find that *platform diffusion* has a strong and negative effect on flop games ($p < 0.01$) and a negative but non-significant effect on star games. Put differently, we find that progressing through an entire platform lifecycle widens the gap between the unit sales of flop games and star games by 17% ($p < 0.05$)—at the expense of less popular games. We find similar results for the effect of *next generation IB*. The growth of a next generation platform's installed base has a more negative effect on the sales of flop video games ($p < 0.01$) than it has on the sales of star video games ($p < 0.05$). A 10% increase in a next generation console's installed base increases the gap in sales between flop and star games by 1% ($p < 0.01$)—again, at the expense of less popular games. The fact that the results show that the negative effect of both proxies for the changing composition of the user base disproportionately affects lower selling games is strongly consistent with our earlier assertion that late adopters fear purchasing games that they do not like.

The control variables show some interesting patterns. First, we find that the effect of *platform* *sales* is 20% more positive for star games than it is for flop games ($p < 0.05$). While *platform sales* has a positive effect on popular games' sales ($p < 0.01$), it has no such effect on less popular games. Analogous to prior studies studying the scope of network externalities on platform demand (Binken and Stremersch 2009), our findings suggest that star complements enjoy stronger network externalities than flop complements, all else being equal. Second, we find that *genre competition* has a 5% more negative effect on flop games than it does on star games ($p < 0.01$). While *genre competition* negatively affects flop games' sales ($p < 0.01$), it has no effect on star games. We thus find that star games are more or less immune to the effects of competitive crowding, which echoes some of the findings reported by Boudreau et al. (2011). Notably, the effect of *new IP* is similar for star and flop games. These findings show that, compared with *existing IP* games, *new IP* games do not vary in their effect on games' sales distribution. In other words, our hypothesized effects on the widening sales gap between high and low selling games are not confounded with differential effects of *new IP* and *existing IP* games on sales.

Addressing Alternative Explanations and Robustness Tests

The theoretical explanation for our findings hinges on the idea that early adopters of a platform differ from later adopters, and that these differences affect complement performance. Compared with later adopters, we propose that early adopters will be more willing to spend on complements and will be more tolerant of risk and novelty. While our results are consistent with this explanation based on demand heterogeneity, we cannot measure consumers directly and so have only indirect evidence. Below we consider multiple alternative explanations for the results to strengthen our claim that our results are indeed driven by heterogeneity in demand.

Game Fixed Effects and Matching

One concern is that the above models are inherently cross-sectional and that they compare very different types of games. Publishers may strategically time the release of different types of video games, anticipating higher sales volumes at different points in the platform lifecycle. Furthermore, as the costs for acquiring platform-specific system development kits (SDKs) fall over time, producers with smaller production budgets—and, subsequently, lower sales thresholds—may seize the opportunity to enter a platform as entry barriers become smaller. We address these concerns by exploiting the multi-homing nature of many games in our sample (52% of all observations). Since *platform diffusion* and *next generation IB* are different for each platform at the same moment, we can use a game-level fixed effects specification that works solely off this cross-platform (but within game) variation. This approach allows for a relatively clean identification of the effect of our shifting user base proxies on game sales.

We run an OLS regression on the subsample of all 640 games that multi-home. Game and platform dummies aside, we only retain the variables from our previous models that exhibit within-game variation (i.e., the main effect of *new IP* as well as other indicator variables are redundant). Estimation results are shown in Table 5. Model 1 includes game and platform fixed effects, Model 2 adds control variables for direct and indirect network effects, Model 3 adds *platform diffusion*, and Model 4 includes *next generation IB*. Model 4 explains 90% of the within-game variation in our dependent variable.

--- INSERT TABLE 5 HERE ---

In Model 4, we again find results consistent with H1 using both proxies for the platform's changing user base. The effect of *platform diffusion* on games' unit sales is much more pronounced in the fixed effects specification. Games that are released on fully diffused platforms have nearly 58% lower unit sales than identical games on new platforms ($p < 0.01$). We find similar results for *next generation IB*. Specifically, we find that a 10% increase in the installed base of a same brand next generation platform correlates with a 1% drop in game sales on the current generation platform ($p < 0.01$). These results isolate the demand heterogeneity effect from a potential "late complementor effect," as they show that an identical game attains higher sales performance on less diffused platforms (vs. more diffused platforms) after controlling for same-side and cross-side network externalities. Among control variables, the only notable result is a finding of no effect for *genre competition* on game sales. We conjecture that this finding can be explained by the lack of within-game variation in *genre competition* across platforms.

The within-effects specification compellingly identifies the effect of the platform's changing user base on game sales, but does not fully account for publishers' potentially non-random resource allocation strategies. Specifically, publishers that successfully launch new IP early in the platform lifecycle may later exploit this IP by creating sequels. This would leave the production of innovative games late in the platform lifecycle to less shrewd producers. To further assess the differential effect of the changing user composition between games that are based on *new IP* and those that are based on *existing IP*, we run a splined-sample matched-pairs estimation. Using PSM, we link each *new IP* video game to its most similar *existing IP* counterpart within every decile of the *platform diffusion* variable.[13] Our analyses yield 10 coefficients that illustrate the relative effect of *new IP* on the log of games' unit sales contingent on the extent of platform diffusion. Full results are available from the authors upon request, but the core results are shown in Figure 3. Consistent with H2, the results show that games based on *new IP* perform relatively well initially but realize progressively lower unit sales relative to comparable *existing IP* games at later periods in the platform lifecycle.

--- INSERT FIGURE 3 HERE ---

Additional Explanations and Robustness Tests

Finally, we consider additional explanations and offer robustness checks. Below, we briefly summarize some of the key investigations, with additional detail and results included in the Online Appendix.

One concern is that consumers face a budget constraint, meaning that they purchase more games soon after buying the platform and buy progressively fewer games over time. Based on our analysis and our interviews in the industry, we definitely agree that per-period purchases for any given user typically decline after platform adoption, but we do not believe that this factor alone can explain our empirical results. One reason is that our time-limited control for installed base controls for budget constraints by excluding some early purchasing adopters from the later installed base. The question is how long of a window to use to calculate installed base. Our results are consistent for windows as short as one month

[13] We rely on observable product characteristics for our matching algorithm. Within every decile of the *platform diffusion* variable, we link each *new IP* game to its closest resembling *existing IP* counterpart on the basis of the following inputs: *game quality*, *platform exclusive*, *game genre*, *publisher*, *platform of release*, *month of release*, *platform sales*, *genre competition*, and *next generation IB*. Running the matching estimation on the full sample of 2,918 games shows that *new IP* games have 51% lower unit sales than *existing IP* games ($p < 0.01$).

and as long as the full installed base (Table A1 R1). Additionally, we have controlled for the average game library size per platform adopter at the time of a focal game's launch (total games sold divided by total platforms sold), which controls for the number of games most users have already purchased at any given point. The results are consistent (Table A1 R1). Another concern is that per-game sales drop because game developers raise new game prices over time. We receive consistent results from models controlling for average selling price, switching our dependent variable to cumulative revenues (instead of units), and predicting our main DV of revenues while controlling for average selling price (Table A1 R2).

Beyond these considerations of alternate explanations, we have conducted a number of additional robustness checks that all produce consistent results. First, one concern is that our findings may be driven by a few high-selling games released at the very beginning of the platform lifecycle, or by low-selling games released at the tail-end of the platform lifecycle when users lose interest in the platform (e.g., because they plan on migrating to a next generation platform). We address this by restricting our sample to exclude the first decile of platform diffusion or excluding all periods after the introduction of any next generation console (Table A1 R3). A related concern is that our *next generation IB* measure is too coarse as it equals zero for many observations. We have used a simple dummy to denote the launch of a next generation console, as well as looking at results only after the launch of the next generation console (Table A1 R3). Second, we ran models using a third proxy for user-base composition by replacing *platform diffusion* with *platform age* (in months). This robustness test addresses concerns that our findings may be driven by our main measure of the platform's changing user-base composition (Table A1 R4). Third, we identified games released at the end of our timeframe that were cross-generation compatible (i.e., multi-homing on seventh generation consoles). While we find that these games perform better than other games released in the same timeframe, our main results largely hold (Table A1 R5). Fourth, we estimated an endogenous treatment effects model of games' selection into *new IP* as an alternative way to control for publishers' non-random resource allocation strategies. In this model we first estimated publishers' decision to launch new IP games and then controlled for this endogenous treatment in the outcome equation. While we find that publishers are less likely to release new IP games later in the platform lifecycle, our main results remain fully supported (Table A1 R5). Fifth, given that we cannot include time fixed effects due to collinearity with *platform diffusion*, we have run models including macroeconomic factors drawn from the UK Office for National Statistics (Table A1 R5). Finally, we used continuous Metascore measures (instead of the categorical measures) as reported on Metacritic. To deal with games with missing quality scores, we alternately use mean-imputation at the platform-year level and drop games without scores (Table A1 R5). In total, these checks give us strong confidence that our observed results are robust to a number of different approaches and specifications.

Discussion

This study extends our understanding of how platform dynamics affect complements by suggesting that complement success is influenced not only by the *number* of users in the installed based but also by demand-side *heterogeneity in preferences and behavior* among those users. Our results suggest that later platform adopters have a lower willingness-to-pay for the platform–complement bundle, are more risk averse, and search differently for complementary goods. These key aspects of heterogeneity lead to lower average performance for complements as the platform evolves, as well as to reduced performance especially for novel complements and an increasing gap between star and flop complements. This allows us to offer the surprising suggestion that more potential users are not always better for providers of complementary goods, as later adopters are largely less valuable than early adopters. We explored these dynamics using a unique dataset of 2,918 sixth generation console video games in the UK, presented empirical results consistent with our theory, and used multiple empirical strategies to discount the potential for alternative explanations. The study allows us to contribute in three specific ways to both research and practice, as discussed below.

First and most directly, this study contributes to the small but burgeoning literature on how platform dynamics affect the success of complements. Boudreau's work has demonstrated the two primary starting points used in this research, namely the important positive effect of a larger installed base and the negative effect of a larger pool of competitors (Boudreau 2012, Boudreau and Jeppesen 2015).

But success is predicated not only on the *volume* of the installed base but also on the *types* of users in that base. By taking a demand-side view on platform evolution, we argued and empirically demonstrated that later platform adopters adopt fewer complements, and that they particularly shy away from complements that are novel and those that are less popular. These findings add to previous work arguing that there is more to network externalities than simply the size of the installed base (Afuah 2013, Lee et al. 2006, Suarez 2005) by emphasizing the importance of user base composition, and add to research promoting an evolutionary perspective on platforms and platform competition (Gretz and Basuroy 2013, Gupta et al. 1999, McIntyre and Srinivasan 2017, Tiwana 2015, Tiwana et al. 2010) by looking at the cross-platform evolutionary effects of the platform on complements. We also show a surprising empirical observation that is in line with prior work (Clements and Ohashi 2005): as the platform matures, we see a high level of video game launches even as the rate of platform adoption declines. This is shown most prominently in Figure 1, where game entries are very high in the last deciles of platform diffusion (a similar, but less dramatic, pattern appears when entry is considered by platform age). This may suggest that complement producers are inert to the slowing rate of platform adoption as the platform nears the end of its lifecycle. The performance implications of such inertia are amplified by the growing share of late adopters on the platform. We believe this observation merits additional study in future work.

Second, this study contributes to the innovation diffusion and demand-side perspectives by articulating specific implications of the various aspects of consumer preference heterogeneity that have been articulated elsewhere. Extensive work has identified differences between early and late adopters, and Rogers (2003) collected these findings in a single source, but the research on the strategic implications of these differences (in platform settings and beyond) is conspicuously thin. As an example of our contribution, by going beyond simply noting that later adopters have a lower tolerance for risk and pushing to articulate the specific implications of those risk preferences, we provide a theoretical foundation for future research to explore how these fundamental differences between early and late adopters affect the viability of other complementary products, technologies, and innovations. Additional work identifying specific aspects of heterogeneity between early and late adopters that seeks to derive specific strategic implications for firms will help to move this stream of literature from a curiosity to an important strategic consideration. One example is the notion of consumer satiation (McAlister 1982, Sevilla and Redden 2014), with the idea that early adopters may become satiated by any given game (and seek out additional games) more rapidly than later adopters, which would correlate with our empirical results in this study. Exploring whether such satiation patterns are valid would be an interesting extension of the research on early versus late adopters. Important for linking demand-side heterogeneity to platform complements is the (entirely reasonable) assumption that adopters' preferences in contingent innovation decisions are stable across innovations (Rogers 2003, Shih and Venkatesh 2004) and time (Andersen et al. 2008, Harrison et al. 2005). Future work would need to explore the extent to which this assumption is true across a wide array of platform and complement types to understand where the boundary conditions of this theory lie. More generally, the recognition that demand-side factors may be relevant not only within a given innovation but across multiple linked innovations (including suppliers, consumers, substitutes, and complements) operating within the boundaries of the same ecosystem presents many potential avenues for future research to explore how the interdependencies between industries has implications for firm strategy and value creation and capture (Adner and Kapoor 2010, 2016).

Third, this study suggests strategic implications for complement providers, platform sponsors, and other players in the platform ecosystem, all of which have practical and research implications. For complementors, this study articulates how early adopters search broadly for complements and are willing to take risks whereas later adopters gravitate towards more certain complements. This creates divergent complementor strategies based on platform lifecycle: early in the platform's existence, firms should focus on throwing gravel by launching a wide variety of complements in new categories, with new technological tools, and using new types of interactivity. This creates incentives for product proliferation that go far beyond those typically articulated as entry deterrents (Bayus and Putsis 1999, Schmalensee 1978). Later in the platform's lifecycle, however, complementors are better off throwing rocks, investing their constrained resources in a limited set of familiar complements that extend efforts made earlier in the platform's lifecycle. This suggests a clear real options based strategy (Adner and Levinthal 2004, Klingebiel and Adner 2015, McGrath 1997) within the platform lifecycle: create a large number of options early, then exploit the successful ones with sequels and spin-offs later. The idea that exploration creates future opportunities to exploit is well known, but the fact that in platform markets firms use this strategy within the lifecycle of a single platform, as opposed to across generations, is new. Understanding the extent to which gravel-throwing firms are more successful at different points in the lifecycle would be an important contribution to our understanding of the evolution of platform based markets. This also has potential implications for platform sponsors, for example how to encourage continuous supply of novel complements throughout the platform lifecycle. While novel complements are essential to platforms' success (Gawer and Cusumano 2014), our findings illustrate the increasing risk of producing novel complements as the platform evolves. At the heart of platform governance strategies are the efforts platform sponsors undertake to ensure that complementors' actions have positive spillover effects on the platform as well as on users (Boudreau and Hagiu 2009, Wareham et al. 2014). Platform sponsors may vertically integrate into the complementor space, restrict certain complementors from entering the platform, and/or strategically promote individual complements. But ecosystem implications transcend the platform–complement pair. For example, our results suggest that the value of a product license from (e.g.) Disney should change over the platform lifecycle, increasing in value with the proportion of later adopters. Do licensors charge different prices based on the platform's lifecycle? If they did, could they extract more value? Future research can explore these and related questions to advance our understanding of how firms should approach platform dynamics.

This study's boundary conditions have important implications for generalizing our contributions. Within the video game industry, we look only at the UK, which is smaller than the US and Japanese markets. The patterns of platform diffusion and game success in the US and UK are very similar, but we still suggest caution in generalizing to all international contexts. For generalizing beyond video games, a central assumption in this paper is that the lifecycle of the complement is shorter than the lifecycle of the platform in which it is embedded. This assumption is valid within games, and it is frequently true across other platforms (e.g., mobile operating systems, crowdfunding, music streaming). If, however, the complement's lifecycle is the same length as the platform or even longer (e.g., Microsoft Word's long lifecycle in the Windows platform), then demand-side dynamics may be different. A complement lifecycle that spans across platform generations may mean that a complement launches to an audience largely composed of later adopters but anticipates the ability to appeal to early adopters when the platform generation shifts. In this case, the strategic dynamics of the complements would be different. Thus, while the idea of exploring how platform user heterogeneity affects complement performance would still be valid for long-lived complements, the exact hypotheses offered here would only be valid when the lifecycle of the complement is shorter than that of the platform.

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Tables and Figures

Table 1. Sixth Generation Video Game Consoles in the United Kingdom (2000–2007)

Platform	Platform sponsor	Launch date	Lifecycle (months)	Avg yearly platform sales	Installed base (mln)	Games launched	Average game sales	New IP ratio	Next gen launch date
PlayStation 2	Sony	Nov-00	85	1,247,307	9.08	1,775	65,810	0.32	Mar-07
Xbox	Microsoft	Mar-02	58	423,968	2.14	738	28,077	0.28	Nov-05
GameCube	Nintendo	May-02	48	254,002	1.05	405	18,156	0.18	Dec-06

Note: All measures based on estimation sample (N = 2,918).

Table 2. Descriptive Statistics and Pairwise Correlations

Variable	Mean	StDev	Min	Max	VIF	1	2	3	4	5	6
1. ln(Unit sales)	9.60	1.72	1.10	14.67	1.14						
2. Platform diffusion	0.62	0.29	0.01	1.00	1.25	-0.20					
3. ln(Next generation IB)	1.24	3.99	0.00	14.64	1.26	-0.17	0.39				
4. New IP	0.29	0.45	0.00	1.00	1.04	-0.19	-0.10	-0.08			
5. Platform exclusive	0.44	0.50	0.00	1.00	1.07	-0.12	-0.07	-0.02	0.15		
6. Genre competition	5.00	3.77	1.00	18.00	1.07	0.06	0.07	-0.07	0.00	-0.07	
7. ln(Platform sales)	13.50	0.85	10.92	14.50	1.17	0.16	0.12	-0.17	0.07	0.16	0.23

Note: Descriptive statistics based on estimation sample (N = 2,918).
Pairwise correlations equal to or greater than |.06| are significant at $p < .05$.

Table 3. The Effect of Platform Diffusion and Next Generation IB on Games Sales

	All games						
	1	**2**	**3**	**4**	**5**	**6**	**7**
ln(Platform sales$_{t-1}$)		0.22**	0.25**	0.11**	0.13**	0.11**	0.12**
		[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]
Genre competition$_{t-1}$		-0.03**	-0.02*	-0.03**	-0.03**	-0.03**	-0.03**
		[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Platform exclusive		-0.10	-0.20**	-0.21**	-0.21**	-0.20**	-0.21**
		[0.07]	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]
New IP		-0.30**	-0.37**	-0.39**	-0.42**	-0.42**	-0.43**
		[0.05]	[0.05]	[0.05]	[0.05]	[0.05]	[0.06]
Platform diffusion			-0.26**	-0.15**	-0.10**	-0.15**	-0.11**
			[0.03]	[0.03]	[0.03]	[0.03]	[0.03]
ln(Next generation IB)				-0.24**	-0.25**	-0.20**	-0.21**
				[0.04]	[0.04]	[0.04]	[0.04]
*New IP * Platform diffusion*					-0.20**		-0.14**
					[0.05]		[0.05]
*New IP * ln(Next generation IB)*						-0.27**	-0.21*
						[0.09]	[0.09]
Quality dummies (3)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Genre dummies (14)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Publisher dummies (71)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Platform dummies (2)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	9.42**	6.79**	5.97**	8.07**	7.76**	8.03**	7.82**
	[0.25]	[0.69]	[0.66]	[0.65]	[0.66]	[0.64]	[0.66]
Observations	2,918	2,918	2,918	2,918	2,918	2,918	2,918
R-squared	0.48	0.49	0.51	0.52	0.52	0.52	0.52

Note: ** $p < .01$, * $p < .05$, + $p < .10$.
OLS regressions of video games' logged unit sales. Variables *Platform diffusion* and *ln(Next generation IB)* are mean-centered to facilitate interpretation of the interaction terms. Heteroskedasticity robust standard errors reported in parentheses.

Table 4. The Effect of Platform Diffusion and Next Generation IB on the Disparity between Star and Flop Game Sales

	All games		
	(τ10) **1**	**(τ90)** **2**	**(τ90-τ10)** **3**
ln(Platform sales$_{t-1}$)	0.04	0.24**	0.20*
	[0.07]	[0.06]	[0.09]
Genre competition$_{t-1}$	-0.05**	0.00	0.05**
	[0.01]	[0.01]	[0.02]
Platform exclusive	-0.38**	0.03	0.40**
	[0.11]	[0.10]	[0.14]
New IP	-0.23*	-0.35**	-0.12
	[0.09]	[0.07]	[0.11]
Platform diffusion	-0.21**	-0.05	0.16*
	[0.05]	[0.05]	[0.07]
ln(Next generation IB)	-0.11**	-0.02*	0.09**
	[0.02]	[0.01]	[0.02]
Quality dummies (3)	Yes	Yes	Yes
Genre dummies (14)	Yes	Yes	Yes
Publisher dummies (71)	Yes	Yes	Yes
Platform dummies (2)	Yes	Yes	Yes
Month-of-release dummies (11)	Yes	Yes	Yes
Constant	8.22**	6.89**	-1.34
	[1.06]	[0.95]	[1.40]
Observations	2,918	2,918	2,918
Pseudo R-squared	0.38	0.32	-

Note: ** $p < .01$, * $p < .05$, + $p < .10$.

Models 1–2: Simultaneous-quantile regressions of flop games (τ10) and star games (τ90). Model 3: Interquantile-range regression estimating the difference in quantiles between star games and flop games (τ90-τ10). Standard errors calculated using bootstrapping method (1,000 draws).

Table 5. Within-Game Effect of Platform Diffusion and Next Generation IB on Game Sales

	All multi-homing games			
	1	**2**	**3**	**4**
ln(Platform sales$_{t-1}$)		0.43**	0.77**	0.67**
		[0.13]	[0.13]	[0.12]
Genre competition$_{t-1}$		0.03*	0.02	0.01
		[0.02]	[0.02]	[0.01]
Platform diffusion			-0.99**	-0.86**
			[0.14]	[0.14]
ln(Next generation IB)				-0.11**
				[0.05]
Game dummies	Yes	Yes	Yes	Yes
Platform dummies	Yes	Yes	Yes	Yes
Constant	12.37**	6.39**	0.03	1.53
	[0.04]	[1.74]	[1.80]	[1.79]
Game-platform observations	1,518	1,518	1,518	1,518
Games	640	640	640	640
R-squared	0.88	0.88	0.90	0.90

Note: ** $p < .01$, * $p < .05$, + $p < .10$.
Fixed effects OLS regressions of multi-homing games' logged unit sales. Heteroskedasticity robust standard errors clustered on the game level.

Figure 1. Distribution of Game Launches and Unit Sales by Game Type

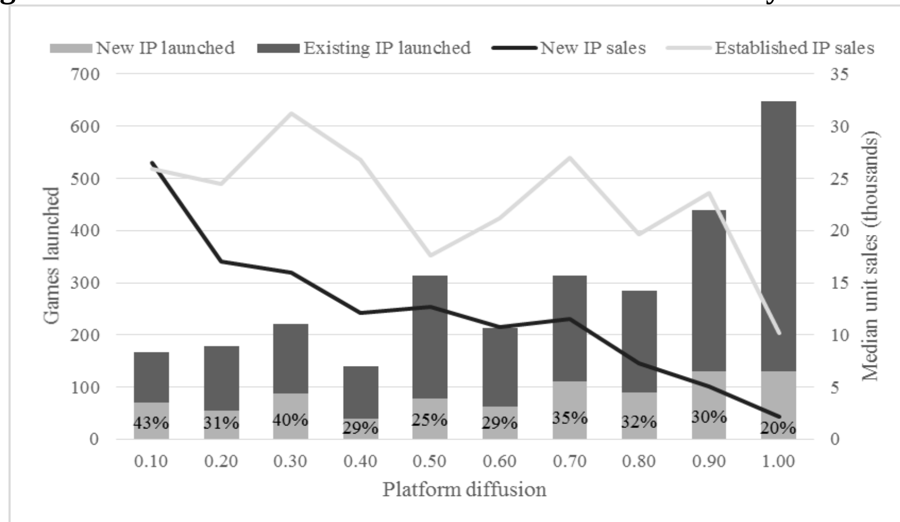


Figure 2. Normalized Video Game Lifecycles by Platform

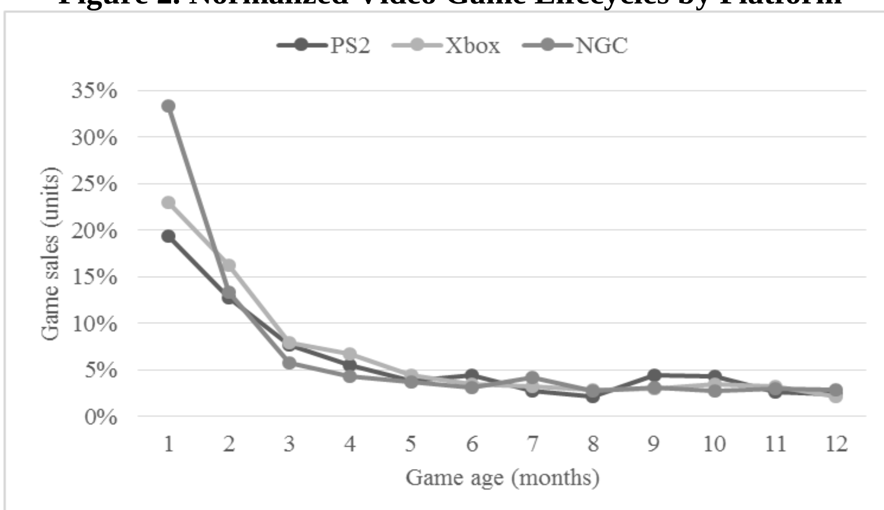
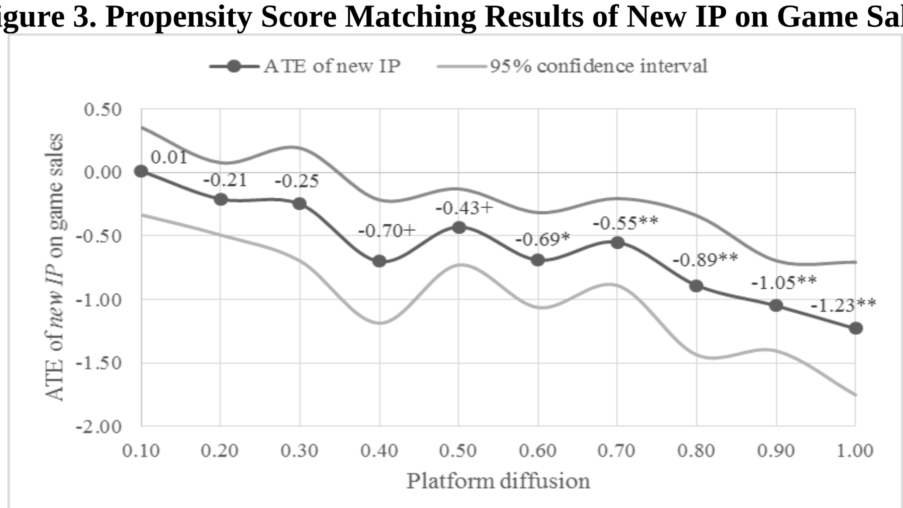


Figure 3. Propensity Score Matching Results of New IP on Game Sales



ONLINE APPENDIX FOR "DEMAND HETEROGENEITY IN PLATFORM MARKETS: IMPLICATIONS FOR COMPLEMENTORS"

Additional Alternative Explanations and Robustness Tests

In the Results section we considered two alternative explanations for our results beyond consumer heterogeneity—the idea that only inferior games launch late, and the idea that only inferior producers produce new IP late. We primarily addressed these through the game fixed effects and matching approaches, respectively, discussed earlier. Other alternative explanations are relatively simply controlled for with our empirical approach. For example, in addition to controlling for game quality, we control for the typical explanations of complementor success of installed base and competitive crowding in our empirical models. But there are a few additional alternative explanations that we seek to identify and discount to further support our story of consumer heterogeneity.

One explanation is that consumers face a budget constraint, meaning that they purchase more games soon after buying the platform and buy progressively fewer games over time. Based on our analysis and our interviews in the industry, we absolutely believe that a budget constraint leading to diminishing game purchases per period for any given user exists in this industry. But we do not believe that this factor alone can explain the totality of our empirical results, for five specific reasons. First, by having a time-limited control for installed base (as opposed to the entire installed base), we are controlling for the budget constraint by excluding some early purchasing adopters from the later installed base. The question is how long of a window to use to calculate installed base. We use one year in our main models based on anecdotal evidence and model fit, but as we show in Table A1 R1 the results are consistent with both a very short window (one month) and a very long window (full installed base). We have tested other windows with similar results. Second, if we overestimate the budget constraint and drop users from the installed base before they stop purchasing games, this effectively undercounts the installed base later in the platform's lifecycle, which should push up the coefficient on platform diffusion. This runs counter to our finding, and therefore seems unlikely to be driving the results. Third, it is unclear why our second measure of user-base composition (the installed base of the next generation platform) should have any effect if everything was driven by a budget constraint. Fourth, a budget constraint cannot explain our results for H2 and H3. Fifth, we tested models including a control for the average game library size per platform adopter at the time of a focal game's launch (total games sold divided by total platforms sold; see Table A1 R1), which controls for the number of games most users have already purchased at any given point. The results are consistent. Thus, we believe that while consumers definitely do purchase fewer games over time, this alone cannot explain the empirical results reported here.

Another explanation is that per-game sales drop because game developers raise their new game prices over time, or other concerns that may be raised around prices. We address these in Table A1 R2, where we first control for average selling price (in GBP), then change our dependent variable to cumulative revenues (instead of units), and then predict revenues including a control for average selling price. The results show that these controls or alternate dependent variables produce similar results.

A final alternative explanation is that late-adopting consumers only buy star games launched early in the platform's lifecycle, depressing sales for later-launching games. Such a concern would be consistent with a social contagion or learning argument. We have two counter explanations to this suggestion. First, our discussions with platform sponsors suggested that this was not the case, as they pointed out that new platform adopters likely bought the platform to purchase newly released games. Second, we do not believe that this explanation is consistent with H2 and H3. In fact, our H3 shows that the gap between stars and flops increases as the platform evolves, but the explanation above would produce the opposite effect—early-launched stars would experience very high sales because later consumers were purchasing the games, while later-launched stars would not have this benefit. Thus, it seems unlikely that this suggestion can address all of the results.

Beyond these considerations of alternate explanations, we have conducted a number of additional robustness checks. First, one concern is that our findings may be driven by a few high-selling games released at the very beginning of the platform lifecycle with the platform sponsor's support, or by low-selling games released at the tail-end of the platform lifecycle when users lost general interest in the platform (e.g., because they plan on migrating to a next generation platform). We addressed these concerns by re-estimating our models on a restricted sample of observations where *platform diffusion* > 0.10, and by re-estimating our models on a restricted sample of observations before the introduction of any next generation video game consoles (Table A1 R3). A related concern is that our current version of *next generation IB* is too coarse since it has the value of zero for most of the observations. To address this issue, we have constructed multiple versions of the *next generation IB* variable. This includes a simple dummy noting whether the next generation console has been launched as well as running our models on a restricted sample where *next generation IB* > 0 (Table A1 R3). Second, we ran our models using a third proxy for user-base composition by replacing *platform diffusion* with *platform age* (in months). This robustness test addresses concerns that our findings may be driven by our main measure of the platform's changing user-base composition (Table A1 R4). The results for all these robustness checks are consistent.

Third, we identified games released at the end of our timeframe that were cross-generation compatible (i.e., multi-homing on seventh generation consoles). While we find that these games perform better than other games released in the same timeframe that are not cross-generation compatible, our main results mostly hold (Table A1 R5). Even though the interaction between *new IP* and *platform diffusion* is reported as statistically insignificant (albeit directionally consistent), the interaction between *new IP* and *next generation IB* is fully supported and significant at $p < 0.01$. Fourth, we estimated an endogenous treatment effects model of games' selection into *new IP* as an alternative way to control for publishers' non-random resource allocation strategies. In this model we first estimated publishers' decision to launch new IP games and then controlled for this endogenous treatment in the outcome equation. While we find that publishers are less likely to release new IP games later in the platform lifecycle, our main results remain fully supported (Table A1 R5). Fifth, given that we cannot include time fixed effects due to collinearity with *platform diffusion*, we have run models including macroeconomic factors drawn from the UK Office for National Statistics. Including the UK GDP as an additional control does not change the results (Table A1 R5). Finally, we have tried an alternative measure of game quality by using the continuous Metascore (instead of the categorical dummies) as reported on Metacritic. To deal with games with missing quality scores, we use mean-imputation at the platform-year level. Our results are fully robust to this alternative measure (Table A1 R5), in addition to dropping games without any Metascores from our sample entirely. In total, these checks give us strong confidence that our observed results are robust to a number of different approaches and specifications.

Table A1. Alternative Explanations

	OLS[1]	FE[2]	OLS[3]	Q-reg[4]
R1: Addressing budget constraint issues				
The effect of *platform diffusion* when platform sales is measured over a one month rolling window	-0.06+ [0.03]	-0.14** [0.04]	-0.16** [0.05]	0.18** [0.06]
The effect of *platform diffusion* when platform sales is measured as the cumulative installed base	-0.11** [0.03]	-0.45** [0.13]	-0.13* [0.05]	0.14* [0.06]
Control for platform adopters' average game library size	-0.20* [0.09]	-0.86** [0.14]	-0.15** [0.05]	-0.25 [0.18]
R2: Controlling for pricing concerns				
The effect of *platform diffusion* with *average selling price* as additional control variable	-0.06+ [0.03]	-0.03* [0.01]	-0.12* [0.05]	0.19* [0.08]
The effect of *platform diffusion* when using *ln(Revenues)* as dependent variable without controlling for average selling price	-0.24** [0.03]	-1.07** [0.13]	-0.17** [0.06]	0.17** [0.05]
The effect of *platform diffusion* when using *ln(Revenues)* as dependent variable with *average selling price* as additional control variable	-0.06+ [0.04]	-1.00** [0.13]	-0.13* [0.05]	0.19** [0.07]
R3: Alternative measures for next gen and censored samples				
The effect of platform diffusion on a censored sample where platform diffusion > 0.10 (N = 2,751))	-0.12** [0.03]	-0.85** [0.14]	-0.12* [0.06]	0.12* [0.06]
The effect of *platform diffusion* on a censored sample before the introduction of next gen consoles (N = 2,303)	-0.11* [0.03]	-0.81** [0.15]	-0.13* [0.05]	0.19** [0.07]
The effect of *next gen IB* on a censored sample after the introduction of next gen consoles (N = 615)	-0.38** [0.10]	-12.84* [6.03]	-0.38* [0.16]	0.44 [0.31]
The effect of next gen when measured as a binary measure (i.e., *next gen introduced* (1/0))	-0.84** [0.13]	-0.45* [0.20]	-0.74* [0.32]	1.26** [0.27]
R4: Platform age as alternative measure for platform diffusion				
The effect of *platform age* when platform sales is measured over a one year rolling window	-0.19** [0.04]	-1.09** [0.23]	-0.21** [0.06]	0.22** [0.07]
The effect of *platform age* when platform sales is measured over a one month rolling window	-0.09* [0.04]	-0.86** [0.24]	-0.18** [0.04]	0.24** [0.08]
The effect of *platform age* when platform sales is measured as the cumulative installed base	-0.14** [0.04]	-0.91** [0.22]	-0.20** [0.06]	0.20* [0.08]
R5: Robustness tests				
Control for cross-generational compatible games	-0.15** [0.03]	-0.86** [0.14]	-0.13* [0.05]	0.12+ [0.07]
Estimate *new IP* via endogenous treatment model	-0.08* [0.03]	-0.86** [0.14]	-0.11* [0.05]	0.08** [0.02]
Control for macroeconomic factors (UK GDP)	-0.13** [0.03]	-0.78** [0.14]	-0.14** [0.05]	0.12+ [0.06]
Control for game quality as a continuous measure (missing quality scores mean-imputed at platform-year level)	-0.62** [0.10]	-0.86** [0.14]	-0.40* [0.18]	0.58* [0.23]

Note: ** $p < .01$, * $p < .05$, + $p < .10$.
[1]Reports the main effect from Model 4 of Table 3.
[2]Reports the main effect from Model 4 of Table 5.
[3]Reports the interaction effect from Model 7 of Table 3.
[4]Reports the interquantile-range regression coefficient from Model 3 of Table 4. All variables of interest are mean-standardized with respect to their focal subsamples to facilitate ease of coefficient interpretation.

Figure A1. UK Installed Base by Platform (2000–2007)