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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 counter-intuitive dynamics for complements. Complements launched early in a platform’s lifecycle face an audience entirely of early platform adopters, while 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 be successful 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 more risk averse late adopters move into the platform and seek to avoid purchasing mistakes.

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"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, shopping malls, and ride sharing services are of limited value to consumers without compatible software, stores, and drivers. This interdependent relationship between platforms and complements leads to strong network externalities – consumers prefer platforms with more complements, and vice versa (Katz & Shapiro, 1985). Platform sponsors such as Nintendo and Uber thus face challenges spurring growth on both sides of the platform (Rochet & Tirole, 2003; Parker & Van Alstyne, 2005), 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 & Santalo, 2013; Schilling, 2002; Suarez, 2004).

Recent research has also begun to explore how network externalities affect competition within platforms, or between producers of complementary goods (Boudreau, 2012; Boudreau & Jeppesen, 2015; Eckhardt, 2016; Yin, Davis & Muzyrya, 2014).\(^1\) 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. Such research on competition within platforms typically builds from the (implicit) assumption that consumers are homogeneous, and that it is the size of the installed base that matters. This study’s primary theoretical argument is that consumers are, in fact, heterogeneous and that systematic differences between consumers who adopt the platform at different points in the platform’s evolution importantly affect competition

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\(^1\) Following previous work on platforms (e.g., Gawer & 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 & Nalebuff, 1997).
between complementors in ways that produce counter-intuitive dynamics.

By adopting a demand-side perspective on platform evolution (Adner, 2004; Adner & Levinthal, 2001; Adner & Snow, 2010), we argue that complements launched early in a platform’s lifecycle face an audience entirely of early platform adopters, while later launching complements face a mixed audience of both early and late adopters. This suggests that whether complements will be successful, 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 & 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. 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.

To analyze these dynamics, we use a unique dataset of 2,918 video games released in the UK from 2000 to 2007 on three competing platforms spanning an entire generation of video game consoles. The market for video games has often been 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 end-users who buy the consoles to enjoy compatible 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 (ESA, 2013; Gartner, 2013). Video game consoles are a particularly fitting setting given their generational nature. Hardware systems have clearly demarcated beginnings and ends, and the timing of competing consoles that are part of the same generation typically occurs within an eighteen months timeframe. 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 – 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 counter-intuitive finding – despite the increase in the potential user pool as the platform evolves, video games launched later in the platform lifecycle actually realize lower unit sales than those launched earlier. While 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 predicting and showing that a larger installed base does not necessarily increase demand for complements when we consider the implications of demand heterogeneity among platform adopters. Thus, to the existing factors affecting complements of a larger installed base and more competitors (Boudreau, 2012; Boudreau & Jeppesen, 2015), we add the effect of different types of consumers. Our findings therefore add to previous work arguing that there is more to network externalities than the size of the installed base (Afuah, 2013; Suarez, 2005) by emphasizing the importance of installed base composition. Our findings also add to research promoting an evolutionary perspective on platform competition (Gawer & Cusumano, 2014) 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,
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 & Kapoor, 2010). 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 articulates 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 & Hagiu, 2009; Wareham, Fox & Giner, 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 such as operating systems and shopping malls the availability of complementary goods affects the success of the platform. Operating systems are only valuable when they are used in conjunction with compatible software applications and shopping malls are only worth attending when there are stores to shop at. 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 stores will boost the number of visitors to a shopping mall. 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 & Ohashi, 2005; Nair, Chintagunta & Dubé, 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 & Jeppesen, 2015), or the effects of product characteristics (e.g., Eckhardt, 2016; Ghose & Han, 2014; Yin, Davis & Muzyrya, 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 start 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. First, complements intuitively draw their sales from a potential user pool comprised 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 a consumer will consider purchasing complements for said platform (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 on complements’ sales
performance has been explored empirically in applications for Personal Digital Assistants (PDA) (Eckhardt, 2016) and online multiplayer video game platforms (Boudreau & Jeppesen, 2015). Thus, we would expect that the number of potential customers (i.e., adopters of a given platform) plays 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 end-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 & 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 & Jeppesen, 2015).

Prior research offers these two factors specific to platform markets that affect complements’ sales performance – the size of the installed base (positive effect) and competition among complements (mostly negative effect). In this study, we explore an additional factor that offers a counter-intuitive theory about the performance of complements as the platform evolves – the 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 their implications for complements’ sales performance – below.

**Effects of Early and Late Platform Adopters on Complements**

Research on the diffusion of innovations has long asserted that there exist key differences between the early and later adopters of an innovation. We recognize that adopter types are actually continuous, but for
sake of exposition we focus on the distinction between two groups – early adopters and late adopters. 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 preferences, preferences for novelty, and search processes. These factors have been shown to differ systematically between early and late adopters, providing an important window into customer preferences that are typically difficult to assess.

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, oftentimes 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 end-users and producers of complementary goods) strongly affects the value of a platform (Brynjolfsson & Kemerer, 1996), but it is often unknown to early adopters which platform will eventually enjoy the highest adoption rate (Katz & 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, and then subsequent 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 do not purchase the platform 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 & 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. This effect, of course, presumes the ability to control for the two known factors that affect complement sales (the size of the installed base and the 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 that more platform users is always better. We thus argue that:

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 as the user base shifts, or different types of complements could suffer disproportionally relative to other types of complements. 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. We first focus on the fact that 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 and uncertain innovation before others in part because they have a greater tolerance for risk. Leonard-Barton (1985) notes that this aversion of uncertainty may be due to late adopters often having less disposable income than early adopters, and so have more at risk with any given innovation decision.
This is importantly related to the concept of novelty seeking. 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. Vishwanath (2005) explores preferences and adoption timing across a number of technology hardware products and found that tolerance for novelty was 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 hearkens back to Rogers’ (2003) statement that early adopters need to handle ambiguity well, as novelty has been defined a key aspect of ambiguity. 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.

Novel complements, however, are likely to struggle as the platform’s user base is comprised of more and more late platform adopters. Similar to newly launched platforms, novel complements are shrouded by uncertainty and are unprecedented, thus imposing valuation ambiguities. This makes them both high risk and highly novel, which means they will appeal to early adopters more so than they do to late adopters. Our second hypothesis therefore is:

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.

Finally, we suggest that the risk aversion of later adopters noted above and the lack of technological sophistication inherent in the unwillingness to explore novel options create important
differences in how later adopters search for and select between competing innovations. Later adopters are uncertain about an innovation’s benefits, and therefore are more cautious in making adoption decisions (Taylor & Todd, 1995). 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. In some contexts, these signals may be familiar brand names (Eggers, Grajek & Kretschmer, 2016), while in other contexts this difference in search behavior may be linked to reliance on expert opinions in making choices (Wijnberg & Gemser, 2000). This inherent difference in search behavior between early and late adopters will likely affect the relative demand for the most and the least popular complements on the platform (i.e., affecting the distribution of cumulative sales across complements). 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 to purchase and should be less concerned about the risks of adopting a complement that they end up not liking (Hirschman, 1980). The result is that 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 and partially-informed later adopters. Note that this process 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. Our third hypothesis therefore is:

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.

Research Setting and Methodology

The Market for Console Video Games in the United Kingdom (2000-2007)
We test our hypotheses in the context of sixth generation console video games in the United Kingdom. The market for video games is a fitting setting for three reasons. First, game consoles are clearly a platform market. The industry includes platform sponsors (e.g., Nintendo) that create the technological infrastructure for video game publishers (e.g., Ubisoft) to commercialize content, and end-users who buy the consoles to enjoy compatible games. End-users are generally attracted to the platform with the highest number of games available, while game publishers prefer to enter the platform with the largest user base. As with most platforms, console sponsors generate revenues through console sales to consumers and through royalty payments from third-party game publishers that wish to tap into the platform’s user base.

Second, video 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 with variation in the types of games and their market performance (see Figure 1, discussed below).

The UK market makes sense as a setting because it is one of the top three geographic markets for video game consumption worldwide. Market analysis conducted by the Independent Development Group (IDG, 2011), for example, finds that the UK market for console video games (hardware and software combined) totaled $3.7bn in 2010, and was only exceeded by Japan ($5.6bn) and the US ($16bn). Our focus on video games in the UK provides an additional benefit in terms of identification: given that (1) game development occurs globally with hotbeds in the US, Japan and UK (Johns, 2006), (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. Nevertheless, we do believe that our results would hold in other geographical markets such as the US and Japan as general trends in consoles’ market shares and consumers’ overall tastes for video game content are largely consistent across these markets.

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 to 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 most supported console 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 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.

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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). 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, (2) median sales of both types of video games decline as the platform becomes more diffused, but (3) sales for new IP games decline at a faster rate than sales for existing IP games. The trends in the raw data are thus consistent with our hypotheses, which is encouraging. We next discuss our data and variables in more detail.

Data and Measures

We built a novel dataset of the entire population of sixth generation console video games released in the UK from 2000 to 2007 (2,918 games). Data at the game-platform level were provided by one of the platform sponsors and include unit and revenue sales, release date, genre, and publisher identification. The sell-through data was collected in the last week of 2011 and include over 90% of all (i.e., brick-and-mortar and online) retail transactions in the UK. Video game quality measures were collected from online expert review aggregation database Metacritic.com. Indicator data on video game novelty was hand-collected by three research assistants. Data at the platform level including launch dates and monthly platform sales were also provided by the platform sponsor. Our final 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. 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.

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 & Lederman, 2011; Landsman & 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 fact, 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 comprised 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 of 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 comprised 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. It is important to 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:

\[
\text{Platform diffusion}_{jt} = \frac{\text{Installed base}_{jt}}{\text{Installed base}_j}
\]

The numerator \(\text{Installed base}_{jt}\) measures platform \(j\)’s installed base at time \(t\) of the focal game’s release, and the denominator \(\text{Installed base}_j\) measures the installed base of platform \(j\) at the end of its lifecycle.\(^2\) 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 adopter-type consumers on a current generation platform. The idea of a next generation technology competing with and eventually displacing the current technology is a common phenomenon in video games, mobile phones, and many other technological innovations (Adner & Kapoor, 2010; Adner & Snow, 2010). Prior research in PDA devices (Kim & Srinivasan, 2009) and smartphones (Huh & 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 is introduced and 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 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

\(^2\) Following previous empirical work we denote the end of a console’s lifecycle when monthly platform sales fall below a certain threshold of 1,000 units, or when we observe a month without any game introductions (Binken & Stremersch, 2009; Cennamo & Santalo, 2013; Landsman & Stremersch, 2011).
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, intellectual property (IP). Video game publishers see creating new IPs as the fundamental innovation activity in their industry. Therefore and following Tschang (2007), we operationalize novel games as those that are based on original intellectual property 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 video games’ box covers and other online sources to understand if the video game was based on a new intellectual property. In our sample, 29% of all video games are based on new IP. This corresponds with generally accepted statistics of non-imitative or truly new innovations in a market (Kleinschmidt & Cooper, 1991). Figure 1 above displays the distribution of video game introductions by type against the diffusion of the platform. The figure illustrates that though 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 terms of 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.

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 need to control for these factors in order 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 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 of time since buying the platform. While our results are robust to using the entire platform installed base, 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 (the un-lagged variable produces similar results). 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.

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, with 100 indicating 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” (0.75 or higher, $n = 787$), “average” (0.50-0.75, $n = 1139$), “bad” (< 0.50, $n = 146$), 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. However, our results are fully robust to a continuous measure of game quality.

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 & Lederman, 2011; Landsman & 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, in order to control for systematic variation in consumer preferences across game genres we include 14 genre dummies. 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 eleven month-of-release dummies excluding January as base. We further control for heterogeneous resources and capabilities (e.g., game engines, marketing capabilities, etc.) at the firm level by including 71 publisher dummies. Finally, time invariant differences at the platform may also structurally affect game sales and therefore we include two platform fixed effects excluding PS2 as the base category. Our final sample for estimation comprises 2,918 video games on three platforms released across 191 console-months.

**Analytical Approach**

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

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

where the log of game $i$’s cumulative unit sales on platform $j$ is regressed on $\beta X_{ij}$, 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 $\beta_0$ and an error term $\epsilon$. 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 & 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. 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 $\text{Quant}_\tau$, where $\tau = 10$ estimates
less popular games and $\tau = 90$ estimates more popular video games. We then assess the differences
between the coefficients by estimating interquantile-range regressions.

**Results**

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

**Baseline Tests for Hypotheses 1 and 2**

Table 2 lists descriptive statistics and pairwise correlations. Pairwise correlations are as expected and lend
correlational support to our hypotheses. 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, 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 that 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 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 platform triggers 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.

**Additional Tests: Game Fixed Effects and Matching**

Our theoretical explanation for the observed empirical results discussed above hinges on the idea that early adopters of a platform differ from late adopters of the platform, and that these differences affect the sales of complements. When compared to later adopters, early adopters will be more willing to spend on complements and will be more risk-tolerant towards novelty. While the results discussed above are consistent with an explanation based on demand heterogeneity, we cannot measure consumers directly and so have only indirect evidence. Below we consider a number of alternative explanations for the results to strengthen our claim that our results are indeed driven by heterogeneity in demand.

One concern is that the above models are inherently cross-sectional, and compare very different types of games to create our results. 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 System Development Kits (SDKs) fall over time, producers with substantially 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 4. 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 4 HERE ---

We turn to Model 4 for the interpretation of our main results. We again find that our results are 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. Exponentiating the coefficient, we find that games that are released on fully diffused platforms have nearly 58% lower unit sales than identical games on newer platforms (p < 0.01). We find similar results for the next generation IB measure. Specifically, we find that a 10% increase in the installed base of a same brand next generation platform leads to 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.

The within-effects specification compellingly identifies the effect of the platform’s changing user base on game sales, yet it does not fully account for publishers’ potentially non-random resource allocation strategies. Specifically, publishers that successfully launch new intellectual properties early in the platform lifecycle may later deploy an exploitation strategy by releasing sequels and spin-offs based on their successful earlier installments. 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 Propensity Score Matching (PSM), we link each new IP video game to their most similar existing IP counterpart within every decile of the platform diffusion variable. Our analyses yield ten 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 coefficients of interest, their significance levels, and 95% confidence intervals are shown in Figure 2. The results clearly 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. These findings are thus fully consistent with H2.

--- INSERT FIGURE 2 HERE ---

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 5 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 5 HERE ---

The results reported in Table 5 are consistent with H3. We find that platform diffusion has a strong and negative effect on flop games (p < 0.01), while it has 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.

**Discussion and Conclusion**

This study extends our understanding of how platform dynamics affect complements by suggesting that complement success is not only influenced by the number of users in the installed base, but also by demand-side heterogeneity in preferences and behavior among those users. The fact 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 leads 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 & Jeppesen, 2015). But success is not predicated only on the volume of the installed base, but also on the types of users in that base. By taking a demand-based view on platform evolution, we argued and empirically demonstrated that later platform adopters adopt fewer complements, and 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; Suarez, 2005) by emphasizing the importance of user base composition, and add to research promoting an evolutionary
perspective on platforms and platform competition (Gawer & Cusumano, 2014) by looking at the cross-platform evolutionary effects on complements.

Second, this study contributes to the innovation diffusion and demand-based 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 (e.g., a strong preference for complements that are familiar in some important way), 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. Importantly 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 & 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.

Third, this study suggests specific strategic implications for complement providers, platform sponsors, and other players in the platform ecosystem, all of which have both practical and research oriented implications. In terms of complementors, this study articulates 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 complements in new categories, with new technological tools, and using new types of interactivity. This
creates incentives for a product proliferation strategy that go far beyond those typically articulated as entry deterrents (Bayus & Putsis, 1999). 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. 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 competition in platform-based markets and beyond. This perspective 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 & Cusumano, 2014), our findings as well as the paper’s opening quote by the CEO of Ubisoft 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 sponsor as well as on the platform’s end-users (Boudreau & Hagiu, 2009; Wareham et al., 2014). But the implications go beyond the platform-complement pair within the ecosystem. For example, the results of this study suggest that the value of a product license from Disney (for example) should change over the lifecycle of the platform, increasing in value as the proportion of later adopters in the installed base increases. Do licensors charge different prices based on the platform’s lifecycle? If they did, could they extract more value from the industry? Future research can explore these and related questions to advance our understanding of how firms should approach platform dynamics.

References

IDG (2011) IDG Global Forecast Update. Trade publication.
### Tables and Figures

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

<table>
<thead>
<tr>
<th>Platform</th>
<th>Platform owner</th>
<th>Launch date</th>
<th>Lifecycle (months)</th>
<th>Avg yearly platform sales</th>
<th>Installed base (mln)</th>
<th>Games launched</th>
<th>Average game sales</th>
<th>New IP ratio</th>
<th>Next gen launch date</th>
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<td>85</td>
<td>1,247,307</td>
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<td>18,156</td>
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Note: All measures based on estimation sample (N = 2,918).

#### Table 2. Descriptive Statistics and Pairwise Correlations

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<td>ln(Next generation IB)</td>
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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 Game Sales

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<td>[0.03]</td>
<td>[0.03]</td>
<td>[0.03]</td>
<td>[0.03]</td>
<td>[0.03]</td>
<td>[0.03]</td>
<td></td>
</tr>
<tr>
<td>ln(Next generation IB)</td>
<td>-0.24**</td>
<td>-0.25**</td>
<td>-0.20**</td>
<td>-0.21**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.04]</td>
<td>[0.04]</td>
<td>[0.04]</td>
<td>[0.04]</td>
<td>[0.04]</td>
<td>[0.04]</td>
<td></td>
</tr>
<tr>
<td>New IP * Platform diffusion</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.20**</td>
<td>-0.14**</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>[0.05]</td>
<td>[0.05]</td>
<td></td>
</tr>
<tr>
<td>New IP * ln(Next generation IB)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.27**</td>
<td>-0.21*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>[0.09]</td>
<td>[0.09]</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
<th>All multi-homing games</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(Platform sales_{t-1})</td>
<td>0.43**</td>
<td>0.77**</td>
<td>0.67**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.13]</td>
<td>[0.13]</td>
<td>[0.12]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Genre competition_{t-1}</td>
<td>0.03*</td>
<td>0.02</td>
<td>0.01</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.02]</td>
<td>[0.02]</td>
<td>[0.01]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Platform diffusion</td>
<td>-0.99**</td>
<td>-0.86**</td>
<td></td>
<td>-0.11**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.14]</td>
<td>[0.14]</td>
<td></td>
<td>[0.05]</td>
<td></td>
</tr>
<tr>
<td>ln(Next generation IB)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Game dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Platform dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>12.37**</td>
<td>6.39**</td>
<td>0.03</td>
<td>1.53</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.04]</td>
<td>[1.74]</td>
<td>[1.80]</td>
<td>[1.79]</td>
<td></td>
</tr>
<tr>
<td>Game-platform observations</td>
<td>1,518</td>
<td>1,518</td>
<td>1,518</td>
<td>1,518</td>
<td></td>
</tr>
<tr>
<td>Games</td>
<td>640</td>
<td>640</td>
<td>640</td>
<td>640</td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.88</td>
<td>0.88</td>
<td>0.90</td>
<td>0.90</td>
<td></td>
</tr>
</tbody>
</table>

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.
Table 5. The Effect of Platform Diffusion and Next Generation IB on the Disparity between Star and Flop Games’ Sales

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

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

![Distribution of Game Launches and Unit Sales by Game Type](image)

Figure 2. Propensity Score Matching Results of New IP on Game Sales

![Propensity Score Matching Results of New IP on Game Sales](image)