Complements Adoption in Two-Sided Markets:
Evidence from the UK Market for Console Video Games (2000-2007)

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ABSTRACT

This paper investigates the adoption of complements in two-sided markets in the context of the console video games industry. Two-sided markets comprise two distinct user groups that provide each other with positive consumption externalities. I argue that the magnitude of these cross-platform effects is contingent on evolving customer heterogeneities. More specifically, providers of complementary goods face competing dynamics as the benefits from increments in the installed base may be depressed by an influx of –risk-averse, ill-informed and price-sensitive–late adopters to the platform. The paper seeks to shed light on these competing dynamics by addressing the following research question: How do platform dynamics affect the adoption of complements in two-sided markets? I formulate hypotheses on the overall effect of platform maturity on complements adoption, and its specific effects on innovative complements and ‘superstar’ complements. To test my hypotheses I use a unique dataset of 2,855 sixth-generation console video games released in the United Kingdom (2000-2007). The paper makes contributions to the studies of technological platforms, and to the burgeoning literature on demand-side perspectives in strategic management.

Keywords: two-sided markets, platforms, complementors, demand heterogeneity, video games.
INTRODUCTION

Popular complements in two-sided markets are paramount to a platform’s success. It was the immensely popular video game Tetris that led to Nintendo’s dominance in the handheld video game market with the Game Boy in the early nineties. The American Broadcasting Company quickly realized the importance of quality content in persuading viewers to migrate from black-and-white television sets to color TVs in the early sixties. Licensing exclusive Disney content helped ABC attract a critical mass of color TV adopters. Auction house Christies allegedly paid a guarantee price of $170 million to obtain the rights to the Ganz collection – an assembly of high quality consignments including Picasso’s The Dream from art collectors Victor and Sally Ganz. The presence of sought after pieces draws in a large crowd of potential bidders to the auction whose desire to purchase may spillover to other lots on auction.

Superstar complements -complements of high quality and high popularity- not only benefit the providers of complementary goods, but also positively affect the popularity of a platform. Research on two-sided markets in economics has predominantly centered on how increments in complements affect adoption on the platform side (Armstrong, 2006; Rochet & Tirole, 2003; 2006). Ample evidence proves the existence of indirect network effects: An increase in the number of complements on the platform leads to a temporal surge in platform adoption (Clements & Ohashi, 2005; Parker & Van Alstyne, 2005; Stremersch et al., 2007). More recent studies in management and marketing have looked at the differential effect that heterogeneous complements have on platform adoption (Cennamo & Santalo, 2013; Corts & Lederman, 2009; Landsman & Stremersch, 2011). Binken and Stermersch (2009) find that superstar complements boost platform adoption by 14% on top of “regular” indirect network effects in the market for console video games.
Despite popular complements’ economic relevance, there exists a paucity of research addressing the antecedents of complements adoption in two-sided markets. This paper aims to address this gap by asking the question: How do platform dynamics affect the adoption of complements in two-sided markets? This is an important question to ask and distinctively different from standalone innovation adoption puzzles as discussed by the product lifecycle or dominant design literatures (Abernathy & Utterback, 1975; 1978; Dosi, 1982). Platforms are “evolving meta-organizations” that comprise a core and a periphery (Gawer, 2014; p. 1241). Platform owners (i.e. the core) purposefully govern their platforms by coordinating and federating two distinct set of actors (i.e. the periphery): complementors and end-users. Competitive dynamics between complementors therefore are dictated not only by competition from rival complements, but also by other factors coordinated at the platform the level.

The paper’s main thesis is that the adoption of complements is affected by a growing but changing installed base over the lifecycle of a platform. The evolution of technological innovations is inherently linked to demand heterogeneity (Adner & Levinthal, 2001; Adner, 2002). As platforms mature, end-users increasingly enter the platform where late adopters differ in their characteristics from early adopters (cf. Chao & Derdenger, 2013; Eisenmann et al., 2006; Lee, 2013; Parker & Van Alstyne, 2005). This growing but evolving audience composition has implications for the competition between complementors and the adoption of complements. Increments in the installed base offer complementors a larger addressable market on one hand. Yet on the other, an influx of risk-averse, price sensitive, and ill-informed late platform adopters may depress the adoption of complements at later stages in the platform lifecycle. I formulate hypotheses on the overall effect of platform maturity on complements adoption, and its specific effects on innovative complements as well as superstar complements.
To test my hypotheses I use a unique dataset of 2,855 video games in the sixth generation video game consoles in the United Kingdom (2000-2007). The market for video games has been described as a canonical example of a two-sided market (Cennamo & Santalo, 2013; Clements & Ohashi, 2005; Dubé, Hitsch & Chintagunta, 2010). Game consoles are a particularly fitting setting for studying the effect of demand heterogeneity given consoles’ generational nature. Rival platform owners synchronize the launch of new consoles, and platform generations have clearly demarcated beginnings and ends. Worldwide sales in the video game industry accounted for $65 billion in 2012, greater than the motion picture and the recording industries combined (ESA, 2013). The most popular video game to date is Grand Theft Auto V published by Take 2 Interactive. GTA V generated in excess of $1 billion just after three days from its launch September 17, 2013.

The paper looks to make valuable contributions to the literatures on two-sided markets (cf. Cennamo & Santalo, 2013; Gawer, 2014; Parker & Van Alstyne, 2005), and the burgeoning research on demand perspectives in management studies (cf. Adner, 2002; Adner & Levinthal, 2001; Priem, 2007). The study’s findings offer a first step toward understanding how platform dynamics affect competition between complements. As platforms mature, the benefits from increments in the installed base are offset by an influx of late adopters to the platform. This causes an inverse U-shaped correlation between platform maturity and the adoption of complements. An influx of late adopters to the platform also reinforces the natural monopoly that superstar complements enjoy vis-à-vis less popular complements. Innovative complements suffer a “double jeopardy” from increases in platform maturity. Not only are later adopters less aware of novel complements, their risk adversity and knowledge of other complements wards them off from adopting these complements at the benefit of non-novel complements.
The rest of the paper is structured as follows: The theory section begins by outlining two-sided markets’ unique features and how early platform adopters differ from late adopters. Next, I formulate three hypotheses on complements adoption in two-sided markets. In the research setting and methodology section I describe the market for console video games and give a detailed overview of the data. After highlighting my analytical approach, I present the study’s findings. The paper concludes with a discussion and conclusions section detailing theory advancement, suggestions for future research, and managerial implications.

COMPLEMENTS ADOPTION IN TWO-SIDED MARKETS

Platform owners in two-sided markets act as intermediaries between two distinct user groups: providers of complementary goods and end-users. Platforms are tasked with creating infrastructure and designing a pricing mechanism that entices both market sides to join (Rochet & Tirole, 2003; 2006). Newspapers have to get advertisers and readers to join, shopping malls need to attract retail establishments and shoppers, video game consoles target game developers and gamers, and auction houses such as Christies and Sotheby’s woo consignors of high value art and affluent bidders. Another feature of platform markets is the existence of cross-platform consumption externalities: Providers of complementary goods derive value from the presence of end-users on the platform, and vice-versa (Katz & Shapiro, 1986). The addressable market for complements is dictated by the installed base (i.e. the cumulative number of platform adopters at a given time), whereas a platform’s appeal to end-users is in large part contingent on the variety of complements on the platform.\(^2\)

\(^2\) Platform markets can include more than two sides and thus be multisided. However, for the sake of exposition and in line with most of the extant literature, I restrict myself to platform markets with two sides (cf. Gaware, 2014).

\(^3\) Other factors driving a platform’s installed base include quality of the platform and platform price, as well the composition of the available complements (i.e. exclusive availability to the platform (Corts & Lederman, 2009; Landsman & Stremersch, 2011; Lee, 2013), or superstar status (Binken & Stremersch, 2009)).
Network externalities in two-sided markets can be direct (same-side) and indirect (cross-side), and they may be either positive or negative (Eisenmann et al., 2006; Parker & Van Alstyne, 2005; Stremersch et al., 2007). While indirect network effects are mostly positive, direct network effect can be either negative or positive. The tension between positive and negative direct network effects is particularly pertinent on the complements side. An increase in the number of complements boosts platform utility which leads to higher platform adoption rates. On the other hand, increases in complements variety may lead to competitive crowding, intensifying the competition on a platform (Boudreau, 2012; Gawer & Cusumano, 2014; Stremersch et al., 2007; Venkatraman & Lee, 2004). While Venkatraman and Lee (2004) find that video game developers are less likely to enter crowded video game platforms, at this point we know little about how this tension affects the adoption of complements in two-sided markets.

The presence of indirect network effects imposes a winner-take-all dynamic on platform competition. Platform market shares often stand in marked contrast as competition disproportionately favors the platform that manages to attain a critical mass of end-users and a wide availability of complements in a timely fashion (Schilling, 1999; 2002). This tipping of the market – “the tendency of one system to pull away from its rivals in popularity once it has gained an initial edge” (Katz & Shapiro, 1994; p. 106) - results in nonlinear adoption rates where the slope of the curve grows exponentially with increments in end-users and complements. At some point in the platform’s lifecycle, however, adoption rates inflect as growth of the installed base

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4 An example of a negative indirect network effect is the accumulation of ads for television viewers.
5 It is for this reason that platform owners often subsidize one side in order to quickly ramp up adoption rates on the other. Newspapers subsidize readers sometimes by giving away free newspapers to attract advertisers. Video game platform owners sell their consoles at a loss to quickly build an installed base developers can sell their games to. Mobile operating systems, on the other hand, have lowered barriers to market entry for apps developers to foster an abundant apps ‘ecosystem’ that will attract buyers of smartphones. Platforms derive most utility from subsidizing participants with the highest price elasticity and those whose exclusive participation in the market has the strongest impact on indirect network effects (Eisenmann et al., 2006; Rysman, 2009).
slows down and eventually plateaus. Drivers behind the S-shaped adoption curve for technology platforms can be supply-side focused (i.e. exhaustion of a platform’s development trajectory, or displacement by a superior next generation platform) and demand-side oriented (i.e. saturation of demand, or the presence of “technologically satisfied” customers) (see, Adner, 2002).

**End-user Heterogeneity and Platform Maturity**

Platforms should not be seen as static entities, but rather as “evolving meta-organizations” in which agents’ roles change and affect the pace of competitive dynamics (Gawer, 2014; p. 124). One such change that is widely accepted among platform scholars is the notion of end-user heterogeneity (cf. Chao & Derdenger, 2013; Eisenmann et al., 2006; Lee, 2013; Parker & Van Alstyne, 2005). A growing installed base, a greater variety in complements, and in certain cases, technological enhancements to the platform, trigger a cascading effect where end-users with different characteristics enter the platform as it matures.

Adopters of an innovation can be placed on a continuum ranging from early adopters (“innovators”) to late adopters (“laggards”). Earlier adopters differ from later adopters along three dimensions that Rogers (2003; p. 280) collectively defines innovativeness: “[T]he degree to which an individual ... is relatively earlier in adopting new ideas than other members of a social system.” First, earlier adopters are more risk-seeking than are later adopters. Early adopters of a platform display venturesomeness by choosing a platform without having exact knowledge of the future availability of complements, or whether competition will eventually favor said platform as the dominant design (Schilling 1999; 2003). Secondly, earlier adopters are more prone to seek information and therefore to have greater innovation-specific knowledge than do later adopters. Early platform adopters base their decision as of which platform to choose
more strongly on its technological prowess (relative to rival platforms) than on the variety of complements available on the platform (Clements & Ohashi, 2005; Gretz & Basuroy, 2013).

Third, early adopters are less price-sensitive than are later adopters (Golder & Tellis, 2004). More generally, earlier platform adopters have a more favorable attitude toward change, are better able to cope with uncertainty, and have greater exposure to mass media communication channels than do later adopters (Rogers, 2003).  

The main premise of this paper is that the evolving composition of a platform’s installed base holds important implications for the adoption of complements. More specifically, providers of complementary goods face two competing forces that affect the adoption of complements. On the one hand, surges in the installed base offer complementors a larger addressable market which enhances complements’ potential adoption rates. Yet on the other, an influx of risk-averse, price-sensitive and ill-informed late adopters depresses the adoption of complements at later stages of the platform lifecycle. Complements that are launched early in the platform lifecycle thus face a relatively small installed base composed of adopters with a favorable attitude towards adopting complements. However, as platforms mature, complementors increasingly face a substantively larger addressable market that is composed of end-users with a hesitant attitude towards adopting complements. I argue that as the number of late adopters on the platform overtakes the number

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6 Diffusion processes follow a normal distribution where innovativeness is partitioned in standard deviations from the average adoption time (Rogers, 1958). Similar to a platform’s lifecycle cumulative adoption follows an S-shaped curve where the mean denotes the inflection point. 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, yet exclude non-adopters. It is important to note that the commonly used adopter categories are a conceptual tool and that the underlying dimensions distinguishing early adopters from late adopters are, in fact, continuous.  

7 The implicit assumption here is that as per their characteristics, later platform adopters buy fewer complements than do earlier adopters (whilst having a larger pool of complements to choose from). This assumption holds true in the chosen empirical context: The attach rate of average video game sales to platform adopters for Sony’s PlayStation 2 console declines at exponential decay from 13.27% at \( \text{Platform age} \_{12} \) to 1.27% at \( \text{Platform age} \_{72} \).
of early adopters, the positive effect from increments in the installed base is offset by the composition of the platform installed base. Hence, the paper’s first hypothesis is:

**Hypothesis 1.** Platform maturity will have an inverse U-shaped effect on complements adoption: Complements launched early or late will have lower adoption rates compared to those launched at intermediate stages of the platform lifecycle.

Platform maturity does not affect all complements equal. The most popular complements on a platform not only enjoy the greatest absolute popularity across adopter categories, they also enjoy the greatest relative popularity from adopter categories that are ill-informed and least likely to buy many complements (McPhee, 1963). Complements that enjoy the greatest exposure are at higher “risk” from being discovered by members across all adopter categories. However, due to the systematic heterogeneity that exists between adopter categories, complements with low exposure tend to only be discovered by platform adopters that are more prone seek information about obscure alternatives (i.e. earlier adopters). Furthermore, once an offering gains a slight competitive advantage, social contagion increasingly puts ill-informed adopter categories (i.e. later adopters) at risk from discovering said offering at the cost of alternatives in the marketplace. McPhee (1963) coined this natural tendency towards a disproportional dominance of the popular “natural monopoly.”

Obscure complements are at additional disadvantage when it comes to customers’ purchase decisions. Sociologist William McPhee (1963) found that the larger the proportion of customers who are unfamiliar with an alternative in a competitive market, the less likely the ones who are familiar with it are to choose it. Obscure complements’ disadvantage –that many customers are unaware, and therefore cannot choose it- is therefore amplified by the notion that
the customers who do know of the offering tend to be well-informed of the overall competitive landscape. Informed customers know of many alternatives which reduces the probability of them choosing any option in particular. And, unless an obscure alternative is of superior quality, such complements are at lower risk from being adopted since well-informed customers tend to “know better” (Ehrenberg, Goodhardt & Barwise, 1990). This “double jeopardy” of the obscure has additional implications for the adoption of complements in two-sided markets.\(^8\)

A steady supply of innovation on the complements side creates value for the platform owner and its constituents through indirect network effects (Gawer & Cusumano, 2014). Complementors are tasked with the strategic decision between releasing novel or non-novel complements (Tschang, 2007).\(^9\) Novel complements are shrouded by uncertainty, yet they help shape the identity of a platform and may boost platform sales upon gaining popularity (Boudreau, 2012). Novel complements are unprecedented and as such impose valuation ambiguities to end-users on the platform. By virtue of their equivocality, novel complements impose greater information needs to assess complement quality and fit. It is for this reason that the adoption of novel complements is disproportionately affected by the evolving composition of the installed base. High information needs are particularly problematic for late adopters that tend to be aware of only a small subset of the competitive offerings available in a market. And when

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\(^8\) I am not the first to use McPhee’s theory to predict competitive dynamics in markets with heterogeneous offerings. In her work, Anita Elberse (2008; 2013) uses double jeopardy to debunk the popular theory of the long-tail in digital distribution and to explain the dominance of blockbuster products in entertainment industries such as motion pictures, music and sports. Double jeopardy is recognized by consumer behavior theorists as a “law-like” occurrence in competitive markets (cf. Ehrenberg et al., 1990; Ehrenberg & Goodhardt, 2002).

\(^9\) Examples of novel and non-novel complements in platform markets are: Auction house for contemporary arts Phillips auctions consignments from the primary market (works of arts that have never left the artist’s atelier) whereas Sotheby’s and Christies restrict themselves to the secondary market to include only lots that have a proven transaction history in the art market. Video game developers are faced with the tension between producing games that are based on new intellectual property (IP) or derivatives of existing video franchises (“sequels”) and external media adaptations such as Hollywood films. Newspaper The New York Times largely relies on coverage generated by in-house journalists whereas the free newspaper Metro relies more heavily on licensing externally generated content from news agencies such as Reuters.
they are aware, late adopters’ low threshold for uncertainty will incline them to favor non-novel complements instead. The paper’s second hypothesis therefore is:

Hypothesis 2. As platforms mature, the disparity between novel and non-novel complements’ adoption will increase: Novel complements’ adoption rates will increasingly fall behind those of non-novel complements.

Superstar complements are complements of high quality and popularity, and are paramount to a platform’s success (Stremersch et al., 2007). In their study of superstar software in the US market for console video games, Binken & Stremersch (2009) find that high quality video games that sell in excess of one million units boost platform sales by 167,000 units. The market for complements is “hit-driven” and complements popularity follows a skewed distribution where ordered ranks decline with exponential decay (Boudreau, 2012). My third postulation is that the skewness in the distribution between the popular and the less popular is contingent on the changing composition of a platform’s installed base. More specifically, as late adopters increasingly enter the platform, the natural monopoly that the most popular complements enjoy will become stronger. Later adopters are aware of only a fraction of the available complements and are at higher risk from being exposed to those with a slight competitive advantage. It is for this reason that linear increments in exposure (through better quality, greater marketing budgets, or external consecration) will increasingly lead to disproportionate increments in complements adoption (McPhee, 1963). My third and final hypothesis therefore is that:

Hypothesis 3. As platforms mature, the disparity between popular and non-popular complements’ adoption will increase: Popular complements’ adoption rates will increasingly surpass those of non-popular complements.
I have argued that the underlying diversity in the audience composition of a platform’s installed base has important implications for the competitive dynamics between providers of complementary goods. As platforms mature, the installed base grows and changes composition over time (Chao & Derdenger, 2013; Eisenmann et al., 2006; Lee, 2013; Parker & Van Alstyne, 2005). This presents complementors with two competing dynamics that affect the adoption of complementary goods. On the one hand, platform maturity correlates with a larger addressable market augmenting complements’ potential adoption rates. On the other hand, platform maturity corresponds with an influx of risk-averse, price-sensitive and ill-informed adopters to the platform (Rogers, 2003). Late adopters’ low threshold towards uncertainty depresses the adoption of complements. This underlying demand heterogeneity has three implications for the adoption of complements: (1) platform maturity has a concave curvilinear effect on complements adoption; (2) the adoption disparity between innovative complements and non-novel complements increases as platforms mature; and (3), the adoption disparity between superstar complements and less popular complements also widens as platforms mature.

RESEARCH SETTING AND METHODOLOGY

“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 (Gamasutra, 2012)

The Market for Console Video Games in the United Kingdom (2000-2007)

The console video games industry includes platform owners that facilitate a technological infrastructure for video game publishers to release their games on, and end-users who must adopt
a given console in order to enjoy the video games released on said platform. Platform owners receive a royalty income from every game sold in exchange for the financial risk taken towards designing and commercializing the platform. Platform owners often sell their consoles at a loss to increase end-user adoption early in the platform’s lifecycle. These losses are subsidized by royalty income from independent games publishers and via internally developed game sales. Given the large upfront investments and long recoupment trajectories, platform owners generally release new platforms every 5 – 8 years.

This paper focusses on the sixth generation video game consoles in the United Kingdom. I choose this generation as it is the most recent generation for which data on the full platform lifecycle was available at the time of data collection. Rival platforms in this generation were Sony’s PlayStation 2, Microsoft’s Xbox and Nintendo’s GameCube. Sony was the first to enter the sixth generation in November 2000 followed by Microsoft and Nintendo in March and May 2002, respectively. Sony’s PlayStation 2 was the dominant platform in this generation with over 9 million units sold in the UK and 155 million consoles shipped worldwide. By the end of the sixth generation Sony dominated the market with 74% market-share followed by Microsoft (17% market-share) and Nintendo (9% market-share). The seventh generation video game consoles commenced with the launch of Microsoft’s Xbox 360 in December 2005 followed by Nintendo’s Wii in December 2006 and Sony’s PlayStation 3 in March 2007.\footnote{For a more detailed overview of what is generally described as the “video game console wars” please refer to my industry case study “Nintendo: Fighting the Video Game Console Wars” in ed. Mintzberg et al. (2013).}

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Among the most popular video game franchises of the sixth generation video games are \textit{Grand Theft Auto} (Take 2 Interactive), \textit{FIFA} (Electronic Arts), \textit{Need For Speed} (Electronic
Arts), *Halo* (Microsoft), and *Super Mario* (Nintendo). The most popular game by cumulative units sold was *Grand Theft Auto: San Andreas* (Take 2 Interactive), which was released as a timed exclusive for the PlayStation 2 in November 2004. *Grand Theft Auto: San Andreas* sold in excess of 2.3 million units in the UK. Highly innovative games of superior quality were received with mixed reactions by console adopters. Nintendo successfully launched its new intellectual property (IP) *Pikmin* early on in the lifecycle of its floundering GameCube platform (June 2002). The game sold nearly 70,000 units and received rave expert evaluations averaging 89/100. On the other hand, when the now defunct THQ released the innovative *Psychonauts* close to the end of the PlayStation 2 lifecycle (February 2006), the game sold a meager 12,000 units despite an average expert score of 88/100.

**Data and Measures**

I built a unique and comprehensive dataset of sell-through data for 2,921 video games released in the UK. Data were collected and combined from multiple primary and secondary sources. Video game and console sell-through data come from a series of proprietary databases provided by one of the platform owners. These datasets include information on video games’ release date, average selling price, genre, and publisher identity. Information on game innovativeness was hand-collected from games’ box covers and publicly available sources. Quality measures were obtained from online review aggregation database Metacritic.com/games. Data on instrumental variables come from the US Bureau of Labor Statistics. Table two provides an overview of the study’s main variables and their respective units of analysis. In the section below I describe my measures in greater detail.

--- INSERT TABLE 2 HERE ---
Dependent Variable

Complements adoption is operationalized as a video game’s cumulative unit sales. Game unit sales data include point-of-sale transactions for approximately 90% of all retail transactions in the UK between November 2000 and November 2007 (online retailers included). Data on game sales are complete until January 2012.\textsuperscript{11} The data are comprehensive in that all console video games released in the UK are included. It is not uncommon for publishers to launch the same video game on multiple platforms at the same time, or to multi-home. By measuring unit sales at the platform level I achieve a finer degree of granularity that allows me to zoom in on the effect of a given platform’s maturity on game sales rather than at the industry level. Nevertheless, I will exploit this feature in the data to run a game fixed-effects estimation on the reduced sample of games that multi-home to control for unobserved heterogeneity across games released at different levels of platform maturity. To fit a normal distribution I take the natural log-transformation.

Independent Variables

The study’s primary focus is the effect of platform maturity on complements’ adoption. In order to facilitate a straightforward comparison between the three platforms’ installed bases, I compute a normalized measure of platform maturity at time $t_i$ such that:

$$
\text{Platform Maturity}_{ijt} = \frac{\text{Installed Base}_{ijt}}{\text{Installed Base}_{ij}}
$$

\textsuperscript{11} Given that console video games generally have very short product lifecycles -typically no longer than three months (Binken & Stremersch, 2009, Tschang, 2007)-- I am not concerned with structural biases in the unit sales measure towards the tail-end of a platform’s lifecycle.
The numerator measures the installed base at the time of a focal game’s release while the denominator is the cumulative installed base at the end of the platform’s lifecycle (Stremersch et al., 2007). Following previous work focusing on two-sided markets in the console video game industry I denote the end of a console’s lifecycle when UK hardware sales drop below 1,000 units per month, or when I observe a month without any software introductions for a given platform (Binken & Stremersch, 2009; Cennamo & Santalo, 2013; Landsman & Stremersch, 2011). Using what is essentially a percentage-based measure linearizes S-shaped platform adoption curve. Linearization further allows for a meaningful interpretation of platform maturity’s effect on games’ unit sales in the econometric models. To test for the hypothesized curvilinear effect I include the squared term.

Hypothesis 2 tests the differential effect of platform maturity on novel complements’ and non-novel complements’ adoption. In the market for video games, novel complements are a clearly demarcated and distinct product category. Games that are based on an entirely new intellectual property (IP) -games that are not adaptations of external media (e.g. motion pictures or TV series) and are not a derivative or sequel of an existing video game license (Tschang, 2007)- are identified as novel complements. Data on novel complements were hand-collected. Two graduate students and an industry expert consulted video games’ box covers and various online sources to understand if a video game was based on a new intellectual property or not.13

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12 Note that in their study of the US console video game industry in the same timeframe Binken & Stremersch (2009) and Landsman & Stremersch (2011) use a threshold of 5,000 consoles sold to lineate the end of a console’s lifecycle. Market analysis firm IDG (2011) estimates that the UK market for video game consoles in 2010 was approximately 20% of the US market, hence the threshold of 1,000 units. Neither of the two criteria is fully met for the PlayStation 2 by the end of the available data on hardware sales (November 2007). This forces me to right-truncate PlayStation 2’s lifecycle which may introduce an upward bias in the results.

13 Data were distributed among raters with some overlap to calculate inter-rater reliability kappas. The obtained kappa value (κ = 0.64) is ‘good’ (Fleiss, 1971) or ‘substantial’ (Landis & Koch, 1977).
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. 29% of all video games in the sample are based on new IP. This statistic corresponds with generally accepted statistics of non-imitative or really new innovations in a market (Kleinschmidt & Cooper, 1991). Figure 1 displays the distribution of video game introductions per platform and the ratio of new IP by platform maturity.\textsuperscript{14} In the robustness testing section I address concerns of unobserved heterogeneity between novel and non-novel games over the lifecycle of a video game platform.

Control Variables

I control for the existence of direct and indirect network effects on video games’ unit sales. Platform sales measures the number of consoles sold in month $t_i$ at the platform level. In order to control for reversed causality I introduce a one month lag where I enter 0 consoles sold in month $t_{-1}$. To fit a normal distribution I take the log-transformation which leads to 65 observations dropped in month $t_{-1}$. Platform entry controls for direct network effects on video games’ unit sales. Platform entry counts the number of rival video games introduced in month $t_i$ at the platform level. Here too, to control for reversed causality by introducing a one month lag.

At the game level I control for a video game’s quality as well as its inflation corrected average retail selling price. Video game quality measures were collected from the video games section of review aggregation database Metacritic.com. I collected the average review scores in addition to the number of reviews at the platform-game level for both expert and user reviews. I use these data to compute a combined average quality score for each game. To obtain the game

\textsuperscript{14} Supply of video games is disproportionate to the growth of the installed base toward the end of the platform lifecycle. Games publishers are inert to a slowing down of a growing installed base: Even when the rate of new platform adopters tapers, games publishers keep releasing new games to exploit the existing installed base. This observation is consistent with Clements & Ohashi (2005) who study the US video game industry (1994-2002).
quality measure, I multiply and add up the average expert and user review scores with their respective number of reviews and divide this by the total number of review scores for each game. In accordance with Metacritic’s grading scheme, game quality is an indicator variable that takes the value of 1 if the quality score for a game is equal to or above 75 – including quality scores that are “generally favorable” and games that achieved “universal acclaim” (Metacritic, 2014). In the robustness testing section I experiment with alternative measures of the quality variable including a continuous measure.

To control for systematic variation in consumer preferences for product categories, I include game genre fixed effects.\textsuperscript{15} Structural variation in game sales may be further affected by differences at the publisher and platform levels. In markets for entertainment goods publishers’ marketing capabilities, product portfolios, and their relationships with gatekeepers such as platform owners are known to induce variance in product performance (Caves, 2000; Hirsch, 1972). For this reason I include 90 firm fixed effects for every publisher in the dataset. Time invariant differences at the platform level may also structurally affect game sales. One could think of hardware quality in the form of processor speed or the functionality of software development kits. Consequently, I include two platform fixed effects with Sony’s PlayStation 2 being the omitted category. I control for the introduction of a next generation platform as this expectedly causes a migration of current platform adopters to the new platform which negatively affects game sales. Next generation platform takes the value of 1 in months $t_i$ where the respective platform owner introduced its next generation video game console.\textsuperscript{16}

\textsuperscript{15} There are 15 genres in the data, these are: Action (omitted), fighting, graphic-adventure, music, non-game, platform, puzzle, racing, real game, role playing game, shooter, simulation, skateboarding, sports, and war.

\textsuperscript{16} In the data I observe nine months in which the PlayStation 2 co-existed alongside the PlayStation 3, fourteen months in which the Xbox co-existed alongside the Xbox 360, and no months in which the GameCube co-existed alongside its successor the Nintendo Wii.
Lastly, the video game industry is characterized by strong seasonality as many games are released in the weeks leading up to the Christmas Holiday season. To control for seasonality I include eleven calendar month fixed effects where January is the omitted category.

Notes on Endogeneity

One may raise concerns that platform entry is endogenous, or correlated with the error term. The error term captures unobserved variation in game sales which may be correlated with the number of games entering the platform. The assumption is that producers of console video games are more prone to enter a platform (or to do so with greater intensity) after observing high adoption rates for games on said platform. After all, if “success-breeds-success,” it pays to enter the platform with the highest performing games (Dierickx & Cool, 1989). To control for the potential bias introduced by such endogeneity, I seek instrumental variables that are correlated with the endogenous covariates but uncorrelated with the error term.

I follow Dubé et al. (2010) and Gretz & Basuroy (2013) in their approach of including a cost-side instrument for platform entry. I exploit the fact that nearly half of the games (46%) are

---

17 In similar vein, one could argue that platform sales is an endogenous covariate. Platform sales is in large part determined by the retail price set by the platform owner, which in turn is affected by various cost- and demand-side factors including the popularity of the platform (Clements & Ohashi, 2005). To avoid usage of complex structural equation models that control for the endogeneity in platform price which then controls for the endogeneity in platform sales, I opt for a more efficient model in which the inflation corrected platform price at retail is treated as an excluded instrument for platform adoption. This assumes that other than through platform sales, a console’s retail price in \( t_{-1} \) will have no effect on games’ unit sales in \( t_{-1} \).

A valid cost-side instrument is the currency exchange rate between the country in which a console was produced and the country of study (Clements & Ohashi, 2005; Corts & Lederman, 2009). Since 77% of the consoles sold are produced in Japan, I use the currency rate between the Japanese Yen and the Great Britain Pound as cost-side instrument for platform sales. I lag the exchange rate by one year since the introduction of the PlayStation 2 and the Nintendo GameCube in the UK was behind by approximately one year compared to their launch in Japan. After using Wu’s (1973) test of endogeneity I fail to reject that platform sales is exogenous (\( F = 0.09 \)). Two Stage Least Squares comes at the cost of being potentially biased and less efficient compared to OLS (Woolridge, 2002). I thus proceed with the more efficient just-identified case where only platform entry is instrumented.
produced in the United States.\textsuperscript{18} As a proxy for the cost of producing games I obtain data on Producer Price Indexes (PPI) for video game publishing in the US from the Bureau of Labor Statistics. Anecdotal evidence has it that production cycles were approximately one year for developing and publishing a video game for sixth generation game consoles. Hence, I introduce a one year lag in \textit{PPI games publishing}. The assumption is that increases in the cost of making video games in $t_{-1}$ negatively affect platform entry rates for video games in $t_{-1}$. It is reasonable to state that the cost of making games in the US thirteen months ago does not affect a UK consumer’s decision as of whether or not to adopt a game today. I also experiment with including \textit{platform age}, its squared term, and their interaction with the instrumental variable to isolate platform specific effects. However, under these specifications I fail to accept the null hypothesis that the first stage models are correctly identified.

--- INSERT TABLE 3 HERE ---

Table 3 lists descriptive statistics and Pearson correlation coefficients for the study’s covariates. The final sample for estimation comprises 2,855 observations released over 189 console-months.

\textbf{Analytical Approach}

Empirical analyses rely on reduced form regressions. To understand the effect of platform maturity on video games’ unit sales I estimate variations on the following equation

\[ y_1 = z_1 \delta_1 + a_1 y_2 + u_1 \]

\[ y_2 = z \pi_2 + v_2 \]

\textsuperscript{18} Japan is the second biggest hub for video game production with 20\% of the video games in our sample, followed by the UK, which accounts for 19\% of all games produced.
Where $y_1$ is the dependent variable (game unit sales), $z_1\delta_1$ represents the full vector of exogenous covariates, $y_2$ is the endogenous covariate (platform entry), and $u_1$ is the error term. $y_2$ is a function of all exogenous covariates plus the excluded instrument $z_1$ (PPI games publishing). I use two-stage least squares (2SLS) for obtaining the predicted values for $\hat{y}_2$ which are then used in the second stage instead of $y_2$. I thus re-write the equation of interest as:

$$y_1 = z_1\delta_1 + a_1\hat{y}_2 + u_1$$

I use Wu’s (1973) test of endogeneity to rule out the possibility that the potentially endogenous covariate is in fact exogenous. I reject the null hypothesis that platform entry is exogenous as the F-statistic of 6.67 is statistically significant ($p < 0.01$). Appendix A reports first stage results and offers a more detailed diagnosis of the first stage estimations.

To identify the performance disparity between popular and less popular video games I use weighted least absolute deviation estimators, or quantile regressions (Koenker & Bassett, 1978). Quantile regressions are apt estimators when the researcher is interested in how independent variables affect various points in the distribution of the dependent variable. Estimating and comparing coefficients for observations in the lower quantiles and higher quantiles of the dependent variable allows one to draw inferences about the effect of platform maturity on the adoption disparity between popular and non-popular video games. I report outcomes to estimations $Quant_{25,50,75}$, where $\tau = 25$ estimates non-popular games, $\tau = 75$ estimates popular video games, and the median least absolute deviation estimator ($\tau = 50$) as reference.

Recent work in econometrics has addressed the issue of endogeneity in quantile regression models. Assuming that $D(u_1 + v_2|z)$ is symmetrically distributed, one can use Ma &
Koenker’s (2006) Control Function Quantile Regression to control for unobserved endogeneity in platform entry, where

\[ u_1 = \rho_1 v_2 + e_1 \]

and \( e_1 \) given \( z \) has a symmetric distribution. Since \( \text{Quant}_\tau(v_2|z) = 0 \), I follow Ma & Koenker (2006) in their estimation of the first stage using a least absolute deviations quantile regression where \( \tau_1 = \tau_2 = \tau \). I can then obtain the residuals \( \hat{v}_{i2} \) as a function of \( \hat{v}_{i2} = y_{i2} - z_i \hat{\alpha}_2 \) which are added together with their interaction with the endogenous variable \( y_{i2} \) to the second-stage least absolute deviations estimation. Hence, for the quantile estimations I write

\[ \text{Quant}_\tau(y_{i1}|z_{i1}, y_{i2}, \hat{v}_{i2}) \]

To apprehend the problem of incorrectly computed standard errors from manually computed control functions, I use the bootstrapping method to compute standard errors in both the first and second stage equation (Woolridge, 2007). For all quantile estimations I use 100 draws to compute standard errors.

RESULTS

Models 1-6 in table 4 estimate the baseline model using OLS. I begin by estimating the effect of the various fixed effects on game unit sales in model 1. Model 2 adds control variables and models 3-6 add independent variables following a nested linear approach. Model 7 re-estimates model 6 using Two Stage Least Squares where platform entry is instrumented with PPI games publishing. All models report heteroskedasticity robust standard errors in parentheses.
Let the instrumental variable estimation (model 7) inform our main findings. Hypothesis 1 postulates an inverse U-shaped effect of platform maturity on games’ unit sales. Hypothesis 1 is supported as we observe a positive linear effect from platform maturity (3.88; p < 0.01) and a negative non-linear effect from platform maturity² (-2.52; p < 0.01) on game sales. Early on in a game console’s lifecycle, increases in platform maturity positively affect games’ unit sales as surges in platform adoption create a larger addressable market for video games. However, after a certain point in the platform’s lifecycle, the positive effect of platform maturity on games’ unit sales is depressed as more risk-averse late adopters enter the platform. Figure 2 plots game sales’ fitted average values for each of the deciles of the platform maturity variable.

The instrumental variable estimator lends support to the presence of indirect network effects from temporal surges in platform sales on video games’ adoption rates. We observe a positive effect from increases in platform sales in $t_{-1}$ on game unit sales in $t_{i}$ in model 7 (0.46; $p < 0.01$). A ten percent increase in platform sales in a given month leads to a nearly five percent (4.58%) increase in average unit sales for a video game released in the subsequent month. This finding can be explained by the fact that new platform adopters need games in order to enjoy their console purchases.

We observe a negative direct network effect from rival complements entering the platform in $t_{-1}$ on games’ average unit sales in $t_{i}$. Model 7 states a negative effect of platform entry on game sales (-0.09; $p < 0.05$). This result implies an almost nine percent (8.60%) drop in games’ unit sales following one additional video game entering the platform in month $t_{-1}$. Instrumenting platform entry with the cost of producing video games in the US has important
implications for the reported results. In the exogenous models I find a weakly significant positive effect from platform entry on unit sales (0.01; p < 0.10). Not controlling for the correlation between platform entry and the error term—potentially fostered by publishers’ anticipation of success-breeds-success effects—induces a positive bias on the covariate’s coefficient in models 4-6. In sum, my results are in favor of the “competitive crowding” hypothesis of direct network effects for complements in two-sided markets.

Quality has a positive effect on games’ adoption (0.34; p < 0.01). Video games with an average combined expert and user review score of 75 or higher sell 40.49% more units compared to those games with scores below the quality threshold. The average inflation corrected retail price has a positive effect on games’ unit sales (1.31; p < 0.01). A ten percent increase in retail price leads to a 13.30% increase in game sales. This somewhat counterintuitive finding may be caused by unobserved heterogeneity in the publisher’s pricing strategy. Publishers who fail to gain traction in the marketplace might lower their prices in an attempt to ramp up demand. I deal with this concern in the robustness testing section. Lastly, we observe a strong effect from the introduction of a next generation platform on game sales (-0.98; p < 0.01). The migration of current platform adopters to the next generation platform significantly hurts game sales. Video games introduced in months where platform owners have launched their next generation platforms sell 62.47% fewer units compared to those games introduced before this period. This effect is driven by the introduction of Sony’s PlayStation 3 and Microsoft’s Xbox 360 consoles.

**Novel and Non-Novel Video Games**

Model 7 in table 4 reports a negative correlation between games based on new intellectual property and average unit sales (-0.30; p < 0.01). All else equal, video games based
on new intellectual properties sell 25.92% fewer units compared to non-novel games. Controlling for quality, games based on new IP impose substantively greater uncertainty to platform adopters. This section assesses the adoption disparity between novel and non-novel games as consoles mature. I replicate model 7 using a split-sample analysis of games that are based on new IP and those that are not. The results from the 2SLS estimations are reported in table 5.

--- INSERT TABLE 5 HERE ---

Hypothesis 2 postulates a widening adoption disparity between novel and non-novel games’ as more late adopters enter the platform. Coefficients in table 5 show that the curvature for platform maturity is stronger for games based on new IP’s than those that are not. These results suggest that novel games benefit more strongly from adopters entering the platform early in its lifecycle (novel: 7.29; $p < 0.05$; non-novel: 2.81; $p < 0.05$). However, novel complements are also more severely affected by adopters entering the platform at later stages in the platform lifecycle. The coefficient for platform maturity$^2$ more strongly affects novel games’ unit sales (novel: -4.98; $p < 0.01$; non-novel: -1.80; $p < 0.05$).

--- INSERT FIGURE 3 HERE ---

To further validate this finding I test the joint null-hypothesis that the difference between the platform maturity coefficients in the two subsamples is equal to zero. Wald-tests following a seemingly unrelated regression (SUR) show that there is indeed a difference between the effect of platform maturity ($\chi^2 = 3.75; p < 0.10$) and platform maturity$^2$ ($\chi^2 = 4.98; p < 0.05$) on unit sales between both subsamples. Taken together, these results imply that games based on new IP sell marginally more units early in on a platform’s lifecycle, while later on new IP sells considerably worse than games that are not based on new IP. Figure 3 graphically depicts this.
finding and shows that halfway through a console’s lifecycle, the adoption disparity between novel and non-novel games widens at the cost of novel games. The difference between the predicted unit sales for novel and non-novel video games is significant for 1,605 observations (from 50% platform maturity onward).

**Popular and Less Popular Video Games**

In the final set of regression models I compare both tails of the distribution of the dependent variable to assess if the adoption disparity between non-popular and popular video games increases as platforms mature. Using a manually computed Control Function Quantile Regressions, I regress all covariates on $\tau = 25$ (non-popular games), $\tau = 75$ (popular games), and $\tau = 50$ (the median) as reference. Table 6 reports the outcomes from the quantile estimations.\(^{19}\)

--- INSERT TABLE 6 HERE ---

Hypothesis 3 posits that as more late adopters enter a platform, the adoption disparity between popular and non-popular complements amplifies in favor of the popular. For non-popular video games ($\tau = 25$), *platform maturity* has a downward sloping curvilinear effect as $platform\ maturity^2$ significantly affects games’ unit sales ($-2.48; p < 0.01$). Late platform adopters increasingly shy away from video games residing in the left tail of the distribution. Model 3 in table 6 ($\tau = 75$) reports a positive effect of *platform maturity* on game sales ($3.72; p < 0.05$) and a negative effect of $platform\ maturity^2$ ($-2.23; p < 0.01$) for popular video games. The interpretation of this finding is comparable to the models relating to hypothesis 1 (see above).

\(^{19}\) The models fail to reach convergence with the full vector of covariates. In order to reach convergence I drop the firm and genre fixed effects from the quantile regressions. The firm dummies are supplanted with three firm level variables: A proxy for a firm’s marketing budget and capabilities, the size of the firm’s product portfolio at time $t_i$, and a dummy variable indicating if the publishing firm of the focal video game is the same as the platform owner. See appendix B for further elaboration on these variables.

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The joint implication of these findings –and as depicted in figure 4- is that early in a platform’s lifecycle, the adoption disparity between superstar games and less popular titles is fairly stable. However, as more late adopters enter the platform, customers increasingly congregate around a few key titles at the cost of other games in the market: Popular video games reinforce their natural monopoly at the cost of the less popular games. The adoption disparity between popular and non-popular video games steadily increases from the 4th decile of a platform’s lifecycle onward (2355 observations) supporting hypothesis 3.

Robustness Testing

One may be concerned about unobserved heterogeneity between games released at different points in a platform’s lifecycle. As the costs for acquiring System Development Kits (SDK’s) for a platform fall over time, producers with substantially smaller production budgets – and subsequently, lower sales thresholds- may seize the opportunity to enter a platform late in the platform lifecycle. To apprehend this concern, I restrict the sample to games released on multiple platforms and run a within game (fixed effects) regression. Due to limited variance in the timing between releases of games that multi-home (i.e. most games that multi-home are released on multiple platforms simultaneously (Corts & Lederman, 2009)), it is expected that the statistical power of platform maturity’s effect on sales tapers.

Table 7 reports the outcome of a fixed-effects 2SLS analysis for the 1492 video games that multi-home. In spite of limited variance in platform maturity, I find a positive linear effect of platform maturity (1.67; p < 0.10) and a negative curvilinear effect of platform maturity² (-2.80;
$p < 0.01$) on games’ unit sales, further validating the study’s main hypothesis. It should be noted that in the game-fixed effects specification, game selling price changes direction compared to the study’s main models. All else equal, higher inflation corrected average retail prices have a negative effect on game unit sales (game selling price: $-0.61; p < 0.01$). Other covariates in table 7 directionally align with those reported in the main models in table 4.

Extending the line of thought above, one may be concerned with unobserved heterogeneity between games based on new IP and those that are not. Publishers that establish successful intellectual properties early in a platform’s lifecycle may deploy an exploitation strategy and leave the production of novel games to less shrewd producers. To assess the average treatment effect (ATE) for games based on new IP at various stages in the platform lifecycle, I run a splined sample matched pair regression. Using propensity-scores based on nearest neighbor matching, I link each new IP video game with their closest counterpart in each decile of platform maturity. I include in the matching equation the following covariates: Platform maturity; game quality; game selling price; platform sales; platform entry; and next generation platform. Regression coefficients for all platform maturity deciles are reported in table 8 and plotted in figure 5.

--- INSERT TABLE 8 HERE ---

--- INSERT FIGURE 5 HERE ---

---

\[\text{To further eliminate potential biases caused by heterogeneous pricing policies I re-estimate all models with an alternative dependent variable. Games’ average selling prices could be endogenously determined as a function of their market performance over time. Publishers of initially unsuccessful games may lower their prices in an attempt to ramp up demand. I circumvent this concern by using the log-transformation of cumulative revenues (in GBP) as alternative dependent variable whilst dropping game selling price from the models. Results from this robustness test are identical to those reported in the main analyses.}\]
The overall treatment effect for the full sample is -0.55 ($p < 0.01$). On average, games that are based on new IP sell 42.31% fewer units compared to their nearest non-novel neighbors. Matching thus strengthens the negative effect that *new IP* has on games’ unit sales compared to the 2SLS model. As illustrated by figure 5 however, the ATE grows from 0.16 (n.s.) in the first decile of a platform’s lifecycle to -1.00 ($p < 0.01$) in the final stretches of a platform’s life. In line with hypothesis 2, these results can be interpreted that as platforms mature, games based on *new IP* enjoy increasingly lower adoption rates compared to their non-novel nearest counterparts. There is reason to believe that publishers are aware of and react to such negative performance feedback. Notwithstanding the fact that games that are based on *new IP* tend to be of marginally higher quality ($0.19; p < 0.10$), I find that as platforms mature, publishers increasingly shy away from releasing new IP’s (*Platform maturity*: -1.03; $p < 0.01$).

I assess the robustness of the results to alternative measures for the *game quality* variable. Some games did not receive any review scores ($n=810$). Since critics’ attention for entertainment goods is allocated non-randomly (Hsu, 2006), one may be concerned with potential biases caused by not capturing this variance with the current quality indicator. I re-estimate the models reported in the main results section with an additional indicator variable that takes the value of 1 if a video game did not receive a single review score, and 0 otherwise. This variable adds nuance to the interpretation of the results by making the distinction between games with positive reviews scores, games that did not receive any review scores, and all other games. The coefficient for *no quality* is not significant (-0.09; n.s.) and its inclusion does not structurally alter the results in any given way (*Game quality*: 0.32; $p < 0.01$). In addition, I re-estimate the models with the raw average quality score using the restricted sample of games that received at least one review score. Across all models I obtain results that are consistent with the findings reported above.
Additionally, I take two precautionary steps to rule out issues of simultaneity and spurious correlations. First, I run models where I take different lags and leads for the platform entry and platform sales measures to assure simultaneity is not a concern. Platform entry loses significance and changes direction when lagging the variable by two platform months or by leading it by one month. Platform sales remains positively correlated with game unit sales when lagged by an additional platform month or leading the variable by one month. However, the strength of the effect weakens from \((0.47; p < 0.01)\) in \(t_{-1}\) to \((0.32; p < 0.01)\) in \(t_{-2}\) and \(t_{+1}\).

Finally, to isolate the effect of platform maturity from macro-economic trends on consumer spending, I rerun all models including the annual growth rate of UK’s Gross Domestic Product (GDP). Inclusion of this variable does not change any of the outcomes.

**DISCUSSION AND CONCLUSIONS [TBD]**

**REFERENCES**


**APPENDIX A: FIRST STAGE REGRESSION RESULTS**

This section diagnoses the first stage estimations to evaluate the strength and relevance of the instrumental variable. Instrumental variable *PPI games publishing* measures the average change (in percentage points) over time in the selling prices of video games for games publishers in the US. An increase in PPI implies higher production costs for video game producers and imposes greater barriers to market entry. Taking video games’ production cycles into account, I lag the variable by one year. I expect increases in *PPI games publishing* in *t* to negatively impact the number of games entering the platform in *t*. First stage OLS regression results for the entire sample and split sample estimations are reported in table A-1.
In line with the above, I find a negative effect of PPI games publishing (-0.16; \( p < 0.01 \)). Increases in the costs of making video games in \( t_{-13} \) lead to a decrease in platform entry by games producers in \( t_{-1} \). This result holds when I split the sample between video games based on new IP and those that are not. I utilize the split-sample results to test for monotonicity, the assumption that the instrument treats all affected subjects equally (Angrist, Imbens & Rubin, 1996). A Wald-test comparing the coefficients of the excluded instrument for novel and non-novel complements fails to reject the null hypothesis of monotonicity (\( \chi^2 = 0.03 \)). This result can be interpreted as the instrumental variable affecting games that are based on new IP and those that are not equal. The outcome of an F-test (19.38; \( p < 0.01 \)) shows that the excluded instrument is sufficiently correlated with the endogenous covariate.

First stage estimations for the Control Function Quantile Regressions are reported in table A-2. From the results we can conclude that the excluded instrument affects the lower quantiles (\( \tau = 25: -0.30; p < 0.01 \)) in the distribution of platform entry more strongly than it affects the higher quantiles (\( \tau = 75: -0.11; n.s. \)). Increases in the production costs of video games hinder platform entry in the bottom quantile of the distribution whereas increases in production costs not necessarily hinder platform entry in the upper quantile of the distribution. This validating result is graphically depicted in figure A-1 below.

In short, the lagged PPI Games publishing covariate is a relevant instrument that sufficiently affects the number of games entering a video game. Across all models, the direction...
and significance levels of other variables in the models are as expected. Platform level covariates (i.e. platform sales, next gen. platform, and platform maturity) impact platform entry as expected whereas game-level covariates (i.e. game quality, game selling price, and new IP) do not. These findings further add to the validity of the first stage estimations.

APPENDIX B: FIRM LEVEL CONTROL VARIABLES

The quantile regression models fail to reach convergence with the full vector of firm dummies. This is caused by the large ratio of firm dummies to observations in combination with some firms having introduced a limited number of games to the market. Hence, I supplant the firm fixed effects with three firm level control variables. In markets for entertainment goods, firms’ marketing capabilities, product portfolio compositions, and relationships with platform owners are known to induce variance in product performance (Caves, 2000; Hirsch, 1972). I include the following firm controls in the models reported in tables 6 and A-2:

- **Publisher-platform portfolio**: The count of the number of video games commercialized by the focal publisher at the platform level at time \(t= t_i\). A larger portfolio implies greater experience with the platform as well as increased opportunity to cross-sell existing game adopters other installments in the publishers’ portfolio (i.e. sequels).

- **Firm listed**: As a proxy for available marketing budget, I include a dummy variable that takes the value of 1 if the publisher is listed on one of the major stock exchanges (e.g. NASDAQ, NYSE). Publicly traded firms have greater resource endowments available for marketing activities compared to non-listed firms.

- **Platform owner published**: A dummy variable that takes the value of 1 if a game is published by the focal platform owner. Platform owners have superior technological
knowledge and access to financial resources, and therefore expectedly outperform games published by third-party publishers.
TABLES & FIGURES

TABLE 1
Sixth Generation Video Game Consoles (2000-2007)

<table>
<thead>
<tr>
<th>Video Game Console</th>
<th>Platform Owner</th>
<th>UK Introduction</th>
<th>Platform Lifecycle</th>
<th>UK Launch Price (GBP)</th>
<th>UK Installed Base (1000)</th>
<th>Game Introductions</th>
<th>Next Gen. Introduced (UK)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PlayStation 2</td>
<td>Sony</td>
<td>November 2000</td>
<td>84 months</td>
<td>£ 299.99</td>
<td>9,083</td>
<td>1,775</td>
<td>March 2007</td>
</tr>
<tr>
<td>Xbox</td>
<td>Microsoft</td>
<td>March 2002</td>
<td>57 months</td>
<td>£ 299.99</td>
<td>3,110</td>
<td>738</td>
<td>November 2005</td>
</tr>
<tr>
<td>GameCube</td>
<td>Nintendo</td>
<td>May 2002</td>
<td>48 months</td>
<td>£ 129.99</td>
<td>1,050</td>
<td>408</td>
<td>December 2006</td>
</tr>
</tbody>
</table>

TABLE 2
Variables and Measures

<table>
<thead>
<tr>
<th>Variable</th>
<th>Measure</th>
<th>Unit of analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Y_1$ Game unit sales</td>
<td>Log-transformation of cumulative unit sales.</td>
<td>Game-platform</td>
</tr>
<tr>
<td>$Z_1$ Platform maturity</td>
<td>Normalized measure of a platform's installed base at $t_1$ divided by the platform's cumulative installed base at the end of the platform lifecycle.</td>
<td>Platform-month</td>
</tr>
<tr>
<td>$Z_2$ Game quality</td>
<td>Indicator variable that takes the value of 1 if the Metacritic reported average combined critic and user review scores are equal to or greater than 75/100.</td>
<td>Game-platform</td>
</tr>
<tr>
<td>$Z_3$ Game selling price</td>
<td>The log-transformed, inflation corrected, average retail selling price.</td>
<td>Game-platform</td>
</tr>
<tr>
<td>$Z_4$ New IP</td>
<td>Indicator variable that takes the value of 1 if a game is based on a new intellectual property.</td>
<td>Game-platform</td>
</tr>
<tr>
<td>$Z_5$ Platform sales</td>
<td>The log-transformation of the number of video game consoles sold in $t_{-1}$.</td>
<td>Platform-month</td>
</tr>
<tr>
<td>$Z_6$ Next gen. platform</td>
<td>Indicator variable that takes the value of 1 in $t_1$ where the focal platform owner introduced a next generation console (e.g. PlayStation 3 from March 2007 onward)</td>
<td>Platform-month</td>
</tr>
<tr>
<td>$Y_2$ Platform entry</td>
<td>The count of video games released at the platform level in $t_{-1}$.</td>
<td>Platform-month</td>
</tr>
<tr>
<td>$Z_7$ PPI games publishing</td>
<td>US Producer Price Index (PPI) value for video games publishing in $t_{-13}$.</td>
<td>Platform-month</td>
</tr>
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</table>
### TABLE 3
Descriptive Statistics and Pearson Correlation Coefficients

<table>
<thead>
<tr>
<th>Variable</th>
<th>VIF</th>
<th>Mean</th>
<th>s.d.</th>
<th>Min</th>
<th>Max</th>
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<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
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</thead>
<tbody>
<tr>
<td>1. Game unit sales</td>
<td>-</td>
<td>4953.76</td>
<td>108855</td>
<td>3</td>
<td>2352406</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td>2. Platform maturity</td>
<td>5.02</td>
<td>0.63</td>
<td>0.28</td>
<td>0.02</td>
<td>1</td>
<td>-0.03</td>
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<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>3. Platform sales</td>
<td>2.02</td>
<td>71723.99</td>
<td>74064.98</td>
<td>1300</td>
<td>770820</td>
<td>0.12</td>
<td>-0.23</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. New IP</td>
<td>1.09</td>
<td>0.29</td>
<td>0.45</td>
<td>0</td>
<td>1</td>
<td>-0.13</td>
<td>-0.10</td>
<td>0.08</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Game quality</td>
<td>1.18</td>
<td>0.31</td>
<td>0.46</td>
<td>0</td>
<td>1</td>
<td>0.18</td>
<td>-0.08</td>
<td>-0.02</td>
<td>-0.06</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>6. Game selling price</td>
<td>1.40</td>
<td>21.09</td>
<td>8.33</td>
<td>4.78</td>
<td>119.28</td>
<td>0.27</td>
<td>-0.27</td>
<td>-0.04</td>
<td>-0.19</td>
<td>0.38</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Next gen. platform</td>
<td>1.25</td>
<td>0.09</td>
<td>0.28</td>
<td>0</td>
<td>1</td>
<td>-0.04</td>
<td>0.39</td>
<td>-0.22</td>
<td>-0.08</td>
<td>-0.07</td>
<td>-0.10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8. Platform entry</td>
<td>1.66</td>
<td>19.17</td>
<td>11.87</td>
<td>0</td>
<td>59</td>
<td>0.18</td>
<td>0.13</td>
<td>0.48</td>
<td>0.00</td>
<td>-0.06</td>
<td>-0.15</td>
<td>-0.11</td>
<td></td>
</tr>
<tr>
<td>9. PPI games publishing</td>
<td>4.22</td>
<td>98.00</td>
<td>1.49</td>
<td>93.60</td>
<td>101</td>
<td>-0.03</td>
<td>0.87</td>
<td>-0.27</td>
<td>-0.08</td>
<td>-0.12</td>
<td>-0.28</td>
<td>0.52</td>
<td>0.12</td>
</tr>
</tbody>
</table>

Note: Absolute correlations greater than or equal to 0.05 are significant at $p < 0.01$. 

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Table 4

<table>
<thead>
<tr>
<th>Variable</th>
<th>1 (OLS)</th>
<th>2 (OLS)</th>
<th>3 (OLS)</th>
<th>4 (OLS)</th>
<th>5 (OLS)</th>
<th>6 (OLS)</th>
<th>7 (2SLS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Game quality</td>
<td>0.38 (0.06)**</td>
<td>0.38 (0.06)**</td>
<td>0.37 (0.06)**</td>
<td>0.37 (0.06)**</td>
<td>0.36 (0.06)**</td>
<td>0.34 (0.06)**</td>
<td></td>
</tr>
<tr>
<td>Game selling price</td>
<td>1.26 (0.10)**</td>
<td>1.27 (0.10)**</td>
<td>1.29 (0.10)**</td>
<td>1.29 (0.10)**</td>
<td>1.33 (0.10)**</td>
<td>1.31 (0.10)**</td>
<td></td>
</tr>
<tr>
<td>New IP</td>
<td>-0.30 (0.05)**</td>
<td>-0.32 (0.05)**</td>
<td>-0.31 (0.05)**</td>
<td>-0.31 (0.05)**</td>
<td>-0.30 (0.05)**</td>
<td>-0.30 (0.06)**</td>
<td></td>
</tr>
<tr>
<td>Next gen. platform</td>
<td>-0.95 (0.11)**</td>
<td>-0.62 (0.12)**</td>
<td>-0.58 (0.12)**</td>
<td>-0.58 (0.12)**</td>
<td>-0.53 (0.12)**</td>
<td>-0.98 (0.25)**</td>
<td></td>
</tr>
<tr>
<td>Platform sales</td>
<td>0.30 (0.04)**</td>
<td>0.29 (0.04)**</td>
<td>0.30 (0.05)**</td>
<td>0.24 (0.05)**</td>
<td>0.24 (0.05)**</td>
<td>0.46 (0.12)**</td>
<td></td>
</tr>
<tr>
<td>Platform entry</td>
<td>0.01 (0.00)**</td>
<td>0.01 (0.00)**</td>
<td>0.01 (0.00)**</td>
<td>0.01 (0.00)**</td>
<td>-0.09 (0.04)*</td>
<td>-0.09 (0.04)*</td>
<td></td>
</tr>
<tr>
<td>Platform maturity</td>
<td>0.04 (0.12)</td>
<td>1.16 (0.42)**</td>
<td>3.88 (1.27)**</td>
<td>-1.06 (0.39)**</td>
<td>-2.52 (0.76)**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Platform maturity²</td>
<td>-1.06 (0.39)**</td>
<td>-2.52 (0.76)**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>9.43 (0.24)**</td>
<td>6.00 (0.37)**</td>
<td>2.16 (0.34)**</td>
<td>2.03 (0.67)**</td>
<td>1.91 (0.77)*</td>
<td>2.45 (0.80)**</td>
<td>1.16 (1.09)</td>
</tr>
</tbody>
</table>

Platform fixed effects  YES       YES       YES       YES       YES       YES       YES
Calendar month fixed effects YES       YES       YES       YES       YES       YES       YES
Genre fixed effects      YES       YES       YES       YES       YES       YES       YES
Publisher fixed effects  YES       YES       YES       YES       YES       YES       YES
Observations             2855      2855      2855      2855      2855      2855      2855
(adjustd) R²             0.46       0.55      0.56      0.56      0.56      0.56      0.47

Heteroskedasticity robust standard errors reported in parentheses.
Platform entry is instrumented in model 7.
The first-stage coefficient for instrumental variable PPI games publishing is -0.16 (0.04) p < 0.01.
** p < .01, * p < .05, + p < .10
### TABLE 5
Platform Maturity Effects on Novel and Non-Novel Games

<table>
<thead>
<tr>
<th>Variable</th>
<th>Novel (2SLS)</th>
<th>Non-novel (2SLS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Game quality</td>
<td>0.56 (0.14)**</td>
<td>0.31 (0.07)**</td>
</tr>
<tr>
<td>Game selling price</td>
<td>0.78 (0.19)**</td>
<td>1.49 (0.12)**</td>
</tr>
<tr>
<td>Next gen. platform</td>
<td>-2.22 (0.54)**</td>
<td>-0.61 (0.28)**</td>
</tr>
<tr>
<td>Platform sales</td>
<td>0.71 (0.34)*</td>
<td>0.41 (0.12)**</td>
</tr>
<tr>
<td>Platform entry</td>
<td>-0.22 (0.10)*</td>
<td>-0.04 (0.05)</td>
</tr>
<tr>
<td>Platform maturity</td>
<td>7.29 (3.02)*</td>
<td>2.81 (1.52)*</td>
</tr>
<tr>
<td>Platform maturity²</td>
<td>-4.98 (1.86)**</td>
<td>-1.80 (0.80)*</td>
</tr>
<tr>
<td>Constant</td>
<td>2.37 (2.71)</td>
<td>0.74 (1.22)</td>
</tr>
</tbody>
</table>

Platform fixed effects       YES                         YES
Calendar month fixed effects YES                         YES
Genre fixed effects          YES                         YES
Publisher fixed effects      YES                         YES
Observations                 826                         2029
(adjusted) $R^2$             0.31                         0.51

Heteroskedasticity robust reported standard errors in parentheses.
Platform entry is instrumented in both models.
The first-stage coefficient for PPI games publishing is -0.17 (0.07) $p < 0.05$ for novel games and -0.16 (0.05) $p < 0.01$ for non-novel games.

** $p < .01$, * $p < .05$, + $p < .10$
<table>
<thead>
<tr>
<th>Variable</th>
<th>1 (Q25)</th>
<th>2 (Q50)</th>
<th>3 (Q75)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Game quality</td>
<td>0.40 (0.09)**</td>
<td>0.39 (0.08)**</td>
<td>0.38 (0.07)**</td>
</tr>
<tr>
<td>Game selling price</td>
<td>1.19 (0.13)**</td>
<td>1.52 (0.12)**</td>
<td>1.53 (0.11)**</td>
</tr>
<tr>
<td>New IP</td>
<td>-0.38 (0.08)**</td>
<td>-0.48 (0.07)**</td>
<td>-0.40 (0.08)**</td>
</tr>
<tr>
<td>Next gen. platform</td>
<td>-1.00 (0.28)**</td>
<td>-1.11 (0.29)**</td>
<td>-0.84 (0.46)+</td>
</tr>
<tr>
<td>Platform sales</td>
<td>0.33 (0.11)**</td>
<td>0.44 (0.09)**</td>
<td>0.52 (0.15)**</td>
</tr>
<tr>
<td>Platform entry</td>
<td>-0.03 (0.04)</td>
<td>-0.10 (0.04)**</td>
<td>-0.12 (0.07)+</td>
</tr>
<tr>
<td>Platform maturity</td>
<td>2.30 (1.40)</td>
<td>4.35 (1.29)**</td>
<td>3.72 (1.53)*</td>
</tr>
<tr>
<td>Platform maturity²</td>
<td>-2.48 (0.93)**</td>
<td>-3.22 (0.84)**</td>
<td>-2.23 (0.75)**</td>
</tr>
<tr>
<td>Constant</td>
<td>1.35 (1.27)</td>
<td>1.75 (1.21)</td>
<td>2.57 (1.04)*</td>
</tr>
</tbody>
</table>

Platform fixed effects  YES  YES  YES
Calendar month fixed effects  YES  YES  YES
Genre fixed effects  NO  NO  NO
Publisher controls  YES  YES  YES
Observations  2855  2855  2855
Pseudo R²  0.18  0.21  0.24

Models estimated via weighted least absolute deviations with standard errors obtained via bootstrapping using 100 draws.

The first-stage coefficient for PPI games publishing in medium least absolute deviation estimation is -0.22 (0.04) *p < 0.01.

** p < .01, * p < .05, + p < .10
### TABLE 7

**Within Game Effects of Platform Maturity on Sales**

<table>
<thead>
<tr>
<th>Variable</th>
<th>All games (2SLS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Game quality</td>
<td>0.10 (0.09)</td>
</tr>
<tr>
<td>Game selling price</td>
<td>-0.61 (0.19)**</td>
</tr>
<tr>
<td>Next gen. platform</td>
<td>-0.82 (0.13)**</td>
</tr>
<tr>
<td>Platform sales</td>
<td>0.69 (0.08)**</td>
</tr>
<tr>
<td>Platform entry</td>
<td>-0.07 (0.02)**</td>
</tr>
<tr>
<td>Platform maturity</td>
<td>1.67 (0.67)*</td>
</tr>
<tr>
<td>Platform maturity²</td>
<td>-2.80 (0.76)**</td>
</tr>
<tr>
<td>Constant</td>
<td>4.95 (1.81)**</td>
</tr>
</tbody>
</table>

Platform fixed effects: YES
Calendar month fixed effects: YES
Genre fixed effects: YES
Publisher fixed effects: YES
Game fixed effects: YES
Observations: 1492
(adjusted) R²: 0.88

Heteroskedasticity robust reported standard errors in parentheses.

*Platform entry* is instrumented with *PPI games publishing*: 5.34 (0.92) *p* < 0.01.

** *p* < .01, * *p* < .05, + *p* < .10
<table>
<thead>
<tr>
<th>Platform maturity</th>
<th>Average Treatment Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-10% (n=127)</td>
<td>0.16 (0.23)</td>
</tr>
<tr>
<td>10-20% (n=153)</td>
<td>-0.15 (0.27)</td>
</tr>
<tr>
<td>20-30% (n=220)</td>
<td>-0.39 (0.21)†</td>
</tr>
<tr>
<td>30-40% (n=140)</td>
<td>-0.46 (0.19)*</td>
</tr>
<tr>
<td>40-50% (n=325)</td>
<td>-0.15 (0.17)</td>
</tr>
<tr>
<td>50-60% (n=202)</td>
<td>-0.40 (0.22)†</td>
</tr>
<tr>
<td>60-70% (n=313)</td>
<td>-0.53 (0.19)**</td>
</tr>
<tr>
<td>70-80% (n=285)</td>
<td>-0.52 (0.18)**</td>
</tr>
<tr>
<td>80-90% (n=440)</td>
<td>-0.67 (0.24)**</td>
</tr>
<tr>
<td>90-100% (n=650)</td>
<td>-1.00 (0.24)**</td>
</tr>
<tr>
<td>Full sample</td>
<td>-0.55 (0.08)**</td>
</tr>
<tr>
<td>Observations</td>
<td>2855</td>
</tr>
</tbody>
</table>

Heteroskedasticity robust standard errors reported in parentheses. Propensity-scores based on nearest neighbor matching. Logit coefficients for matching covariates: Platform maturity (-1.03; p < 0.01); game quality (0.19; p < 0.10); game selling price (-1.42; p < 0.01); platform sales (0.15; p < 0.10); platform entry (-0.01; p < 0.01); and, next gen. platform (-0.46; p < 0.05).

** p < .01, * p < .05, + p < .10
TABLE A-1
First Stage Regressions: Platform Entry

<table>
<thead>
<tr>
<th>Variable</th>
<th>Full sample (OLS)</th>
<th>Novel (OLS)</th>
<th>Non-novel (OLS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Game quality</td>
<td>-0.11 (0.27)</td>
<td>-0.36 (0.47)</td>
<td>-0.01 (0.32)</td>
</tr>
<tr>
<td>Game selling price</td>
<td>-0.14 (0.37)</td>
<td>-0.22 (0.62)</td>
<td>-0.28 (0.49)</td>
</tr>
<tr>
<td>Platform sales</td>
<td>1.96 (0.38)**</td>
<td>2.28 (0.78)**</td>
<td>1.91 (0.45)**</td>
</tr>
<tr>
<td>Next gen. platform</td>
<td>-5.41 (0.50)**</td>
<td>-4.64 (1.17)**</td>
<td>-5.76 (0.57)**</td>
</tr>
<tr>
<td>Platform maturity</td>
<td>19.05 (3.09)**</td>
<td>18.33 (5.20)**</td>
<td>18.59 (3.90)**</td>
</tr>
<tr>
<td>Platform maturity²</td>
<td>-11.03 (2.33)**</td>
<td>-11.05 (3.97)**</td>
<td>-10.15 (2.93)**</td>
</tr>
<tr>
<td>New IP</td>
<td>-0.03 (0.24)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PPI games publishing</td>
<td>-0.16 (0.04)**</td>
<td>-0.17 (0.07)*</td>
<td>-0.16 (0.05)**</td>
</tr>
<tr>
<td>Constant</td>
<td>2.77 (6.32)</td>
<td>6.59 (12.49)</td>
<td>0.06 (7.59)</td>
</tr>
</tbody>
</table>

Platform fixed effects: YES
Calendar month fixed effects: YES
Genre fixed effects: YES
Publisher fixed effects: YES
Observations: 2855
(adjusted) R²: 0.78

Heteroskedasticity robust standard errors reported in parentheses.
Excluded instrument: PPI Games publishing
** p < .01, * p < .05

TABLE A-2
First Stage Quantile Regressions: Platform Entry

<table>
<thead>
<tr>
<th>Variable</th>
<th>1 (Q25)</th>
<th>2 (Q50)</th>
<th>3 (Q75)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Game quality</td>
<td>0.00 (0.04)</td>
<td>-0.11 (0.10)</td>
<td>0.00 (0.10)</td>
</tr>
<tr>
<td>Game selling price</td>
<td>0.00 (0.09)</td>
<td>-0.10 (0.13)</td>
<td>0.00 (0.16)</td>
</tr>
<tr>
<td>New IP</td>
<td>0.00 (0.04)</td>
<td>-0.04 (0.08)</td>
<td>0.00 (0.08)</td>
</tr>
<tr>
<td>Next gen. platform</td>
<td>-5.47 (0.87)**</td>
<td>-6.54 (0.65)**</td>
<td>-6.27 (1.75)**</td>
</tr>
<tr>
<td>Platform sales</td>
<td>0.98 (0.38)*</td>
<td>0.82 (0.37)*</td>
<td>1.75 (1.09)</td>
</tr>
<tr>
<td>Platform maturity</td>
<td>17.24 (3.90)**</td>
<td>18.16 (4.26)**</td>
<td>129.3 (6.41)*</td>
</tr>
<tr>
<td>Platform maturity²</td>
<td>-13.76 (2.92)**</td>
<td>-12.01 (2.89)**</td>
<td>-4.10 (5.50)</td>
</tr>
<tr>
<td>PPI games publishing</td>
<td>-0.30 (0.03)**</td>
<td>-0.22 (0.04)**</td>
<td>-0.11 (0.09)</td>
</tr>
<tr>
<td>Constant</td>
<td>18.03 (4.74)**</td>
<td>25.61 (6.64)**</td>
<td>13.82 (16.71)</td>
</tr>
</tbody>
</table>

Platform fixed effects: YES
Calendar month fixed effects: YES
Genre fixed effects: NO
Publisher controls: YES
Observations: 2855
Pseudo R²: 0.56

Models estimated via weighted least absolute deviations with bootstrapped standard errors from 100 draws. Excluded instrument: PPI games publishing.
** p < .01, * p < .05, + p < .10
Figure 1

Game Introductions & New IP Ratio by Platform Maturity

![Chart showing game introductions and new IP ratio by platform maturity.](chart1)

Figure 2

The Effect of Platform Maturity on Game Sales

![Chart showing the effect of platform maturity on game sales.](chart2)
**Figure 3**

Performance Disparity between Novel and Non-Novel Games

![Graph showing performance disparity between novel and non-novel games.](image)

**Figure 4**

Adoption Disparity between Popular and Non-Popular Games

![Graph showing adoption disparity between popular and non-popular games.](image)

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Figure 5

The Effect of New IP by Platform Maturity

Figure A-1

The Effect of PPI Games Publishing on Platform Entry
Complements Adoption in Two-Sided Markets: Evidence from the UK Market for Console Video Games (200-2007)

Figure A-2. Empirical strategy ($t_i = \text{platform age}$)

H1. Independent var. ($t=i$):
- Platform maturity

Dependent vars. ($t=i$):
- Video game unit sales
  A. Average unit sales (log)
  B. Novel & non-novel
  C. High & low popularity (Q25/Q50/Q75)

H2. Independent var. ($t-1$):
- Platform sales (log)†
  ENDONOGENS

H3. Independent var. ($t-1$):
- Platform entry
  ENDONOGENS

H2. Instruments:
- Platform price – inflation corrected (log) ($t-1$)
- JPN¥/GBP£ rate ($t-13$)

H3. Instrument ($t-13$):
- Cost of producing video games in the US (PPI)

Controls ($t=i$):
- Game level controls
  - Quality $\Rightarrow$ 75%
  - Price – inflation corrected (log)
- Publisher fixed effects*
- Platform fixed effects
- Calendar month fixed effects
- Next gen. platform introduced

† Note: Variable treated as exogenous after failing to reject Wu’s (1973) test for endogeneity.

* Note: Firm fixed effects dropped in quantile regression models due lack of convergence. Included firm controls: firm portfolio, firm listed, and platform owner published.