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# Why Quality May Not Always Win: The Impact of Product Generation Life Cycles on Quality and Network Effects in High-tech Markets☆

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**Abstract**

Marketing literature has recently witnessed major debates about the critical drivers of success – namely, the quality versus network effect, in high-tech markets as well as the efficiency of such markets. Extant research suggests that both quality and network effects are significant factors determining market share in these markets, but that quality effect is more important. Based on surveys of several retail managers and a new dataset on the US video game industry from 1995 to 2007, we replicate and extend this research in several directions: (1) we replicate and confirm prior results that both quality and network effects are critical drivers of market share; (2) network and quality effects vary over the product generation life cycle, and hence, quality does not always win; and (3) in the Growth and Maturity phases of the product generation life cycle, network effects can trump quality effects. Our empirical results provide some practical insights for retail managers.


*Keywords:* Network effect; Quality; Efficiency; High-tech products

## Introduction

The purpose of this paper is to examine the relative impacts of quality and network effects over a product generation life cycle in the context of the retail video game industry. The video gaming industry is a significant one for the US and the global economy. According to PricewaterhouseCoopers, the global gaming industry revenues will grow to $82 billion in 2015. Globally, video games racked up $58.7 billion in sales in 2011, substantially more than the global music industry ($49.8 billion). Big video game releases can far outsell a movie launch. Last year, *Call of Duty: Modern Warfare 3* broke $1 billion in sales faster than the 2009 movie, *Avatar*, the highest grossing film of all time (*Wall Street Journal*, November 2, 2012, pp. D1–D2). The market for home video games in US has grown dramatically; annual revenue growth exceeded 9% from 2005 to 2011 (Entertainment Software Association 2011). About 72% of US households play computer or video games, and the average household owns two games. US revenues generated by software sales, console sales, and peripherals exceeded $16 billion, $6 billion, and $2.5 billion in 2011, respectively (Entertainment Software Association 2011).

As a product category, video games consoles and peripherals have played a significant role for major US retailers and manufacturers. For example, the category is responsible for 14% of Best Buy's domestic sales in 2011 (Best Buy 10-K, 2011, page 41). About 12% of Microsoft's revenues accrue from its entertainment division, "which includes the Xbox 360 gaming and entertainment console, Kinect for Xbox 360, Xbox 360 video games, Xbox Live, and Xbox 360 accessories..." (Microsoft 10-k, 2010). Importantly, about 76% of sales of games, consoles and peripherals in the US occur at traditional retail outlets such as Wal-Mart, Target, and Best Buy (Entertainment Software Association 2011). Therefore, many managerial decisions at the retail level (where it is most important) are affected by the relative importance of quality and network effects. The video game industry is a classic example of a networked market with natural product life cycles (consoles) and hence, an appropriate industry for testing hypotheses regarding the relative impacts of quality

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and network effects. The aim of our paper is to provide insights to managers and academics regarding the importance of these effects over a generational life cycle.

Before we discuss the theory and our empirical findings, we wanted to ground our research in practice. With that aim in mind, we surveyed six managers of retail stores – Walmart, Best Buy, RadioShack, and GameStop. In our choice of the managers to survey, we were guided primarily by access and availability. These managers were asked questions such as: How important is the console gaming industry to your business?; Overall, in determining the mixture of consoles you order (e.g. PS3, Xbox 360, Nintendo Wii, Nintendo Wii U, etc.) how influential is (a) quality of console (i.e. technical specifications of the console), and (b) quantity of available games for the console?; When consoles are relatively new (e.g. within the first 6 months of being introduced)/at the midpoint of their life cycle (e.g. between 2 and 4 years after they are introduced)/at the end of their life cycle (e.g. 5 years or so after they are introduced), how influential are the following on the mixture of consoles you order: (a) quality of the console (i.e. technical specifications of the console) and (b) quantity of available games for the console?; and finally, To what extent do you agree with the following statement: "higher quality consoles (i.e. consoles with better technical specifications) have a greater number of available games?" All questions were answered using Likert-type scales, with anchors of 1 (lowest) and 9 (highest).

The responses to our surveys underscored the importance of the video gaming industry for their respective retail businesses, and the importance of console quality in various decisions made regarding product assortment. A manager of Best Buy commented: "Most major consoles receive high ratings or we would not carry them. . .when customers purchase consoles, they also purchase accessories." Importantly, the key idea that emerged from these surveys and interviews is that console *quality* is critically important and that during the life cycle of the console, the importance of the *quantity* of games to the retailer changes. Therefore, we believe that a clearer understanding of the determinants of sales in the video game industry—quality and network effects—will be beneficial to retailers as well as academics.

Recently, marketing literature has witnessed a major debate about the critical drivers of success – specifically regarding quality versus network effect, especially in high-tech networked markets (Ratchford 2009; Reibstein 2009; Rossi 2009; Shugan 2009; Tellis, Yin, and Niraj 2009a; Tellis, Yin, and Niraj 2009b). Tellis, Yin, and Niraj (2009a) demonstrate that both the quality effect and network effect are significant factors for determining market share, but that the quality effect is more important than the network effect. The results of Tellis, Yin, and Niraj (2009a) are important because (i) the traditional theoretical literature on network effects in marketing and economics usually does not consider the quality effect (e.g., see Farrell and Klemperer 2007; Srinivasan, Lilien, and Rangaswamy 2004); (ii) empirical works in the economics literature focus on the network effects to the exclusion of quality effects (see, Gretz 2010b for an exception); (iii) scholars have speculated (often via theoretical models) that network effects can overtake quality, and firms with strong network effects may end up dominating the market by making it difficult for competitors, even with superior product quality, to enter the market (Reibstein 2009). Thus, by showing that product quality dominates in such high-tech markets, Tellis, Yin, and Niraj (2009a) implicitly argue that network effects need not be sufficient barriers to entry.

Our paper contributes to this current literature and the ongoing debate and extends the results of Tellis, Yin, and Niraj (2009a) in several ways. First, we replicate prior research and show that, indeed, both quality and network effects are significant factors in determining market share in high-tech markets. Second, contrary to the relatively stable impact of quality and network effects found in Tellis, Yin, and Niraj (2009a), we show that the quality and network effects vary over the product generation's life cycle. Table 1 highlights this contribution. We list several empirical studies that examine the impact of network effects and other factors (quality, heterogeneous consumers, etc.) on market outcomes. Ours is the only paper that explicitly incorporates different phases of the product generation life cycle.

Third, we show that there are times when the network effect can indeed overshadow the quality effect. Specifically, we find that the network effect may dominate the quality effect during the Growth and Maturity phases of a product generation's life cycle. In our analyses, we jointly estimate both the demand and the supply equations, allowing for backward compatibility of the products (Ratchford 2009); we control for the endogeneity issues raised by Reibstein (2009) and Rossi (2009) by using several reasonable instruments with instrumental variables regression techniques via generalized method of moments (GMM) estimations.

Our study also adds to the recent literature examining indirect network effects in the video game industry. In dynamic models, Liu (2010) shows console makers consider both consumer heterogeneity and indirect network effects in their optimal pricing decisions. Dubé, Hitsch, and Chintagunta (2010), incorporating forward looking consumers, measure the tipping effect associated with indirect network effects. However, both studies focus on only two consoles competing in one generation; neither allows point estimates of quality and network size to vary over the generation life cycle, and console specific effects on market share—console quality—are included as controls but are not the main focus of their research. In fact, both papers include console-specific effects on consumer utility but obtain different results. While neither study finds significant console-specific effects on market share, Liu (2010) finds evidence that Nintendo 64 is of higher quality while Dubé, Hitsch, and Chintagunta (2010) finds evidence favoring PlayStation—and both provide reasonable qualitative arguments supporting their findings.

We enhance the literature by considering a much longer time frame in the video game industry, specifically 12 years (1995–2007) where we observe 4 different product generations. Also, we simplify from their dynamic considerations, as well as heterogeneous consumers (Liu 2010), and forward-looking consumers (Dubé, Hitsch, and Chintagunta 2010), to focus on quality and network effects over the product generation life cycle.

Table 1
Selected empirical literature: papers examining network effects and other factors as indicated.

| | Industry | Phases of the generation life cycle | Product age | Product pre-announcements | Hardware quality | Consumer heterogeneity | Dynamics | Forward looking consumers |
|---|---|---|---|---|---|---|---|---|
| Current study | Video games | X | | | X | | | |
| Clements and Ohashi (2005) | Video games | | X | | | | | |
| Dranove and Gandal (2003) | Digital video discs | | | X | | | | |
| Dubé, Hitsch, and Chintagunta (2010) | Video games | | | | | | X | X |
| Gretz (2010b) | Video games | | | | X | | | |
| Liu (2010) | Video games | | | | | X | X | |
| Nair Pradeep and Jean-Pierre Dubé(2004) | Personal digital assistants | | | | X | | | |
| Ohashi (2003) | Video cassette recorders | | | | X | | | |
| Park (2004) | Video cassette recorders | | | | X | | X | |
| Shankar and Bayus (2003) | Video games | | | | | | X | |
| Tellis, Yin, and Niraj (2009a) and Tellis, Yin, and Niraj (2009b) | Several high-tech industries | | | | X | | | |

In the next section, we briefly review the literature on quality and network effects and propose several hypotheses. Then, we describe the data. Next, we analyze the data and provide the key results. In the final section, we discuss the study's implications and limitations and provide directions for further research.

## Theoretical background and hypotheses

Markets with network effects are special markets that possess the interesting property of network externality. Positive network externalities are said to exist in a market when consumer benefit increases with the number of adopters in a network. These externalities are *direct* when the attractiveness of the network increases directly with the number of consumers in it, such as in a telephone network. An externality is *indirect* when an increase in consumers results in an increase of complementary products provided for the network (Srinivasan, Lilien, and Rangaswamy 2004; Srinivasan, Lilien, and Rangaswamy 2006). Economists have expressed significant concerns that industries characterized by network effects may often tip to a dominant standard or lead to "lock-in" that may favor established and dominant products over newer products that may be superior (Katz and Shapiro 1994).

In the marketing and economics literature, the issue of quality and its importance in driving a product's success have, of course, received significant attention. Liebowitz and Margolis (1995, 1996) provide many industry examples to argue that quality might be the principal driver of market position and that network effects do not necessarily protect players from competition. Their assertions suggest that the network externality may not be sufficient for lock-in and that product quality may have a dominant role to play in generating and maintaining market shares.

A key aspect that plays a significant role in most products and especially in high-tech markets (Buzzell 1966; Day 1981; Golder and Tellis 2004) is the idea of a product life cycle (PLC) and product generations. Because of its critical impact on marketing strategy, the PLC has become a central, enduring framework in marketing. Its intuitive appeal is no longer confined to marketing and the concept is used routinely in many disciplines. Therefore, in a high-tech market, the PLC over a product generation, or product generation life cycle, may play an especially significant role in determining the relative impacts of quality and network effects. This may happen for several reasons.

First, Tellis and Fornell (1988) argue that costs of producing higher quality declines as the product matures. Moreover, businesses tend to produce at optimal quality levels later in the product's life cycle, when consumer response functions are understood better. Second, Shankar, Carpenter, and Krishnamurthi (1999) find that the effect of product quality changes as a brand enters different phases of the life cycle. Specifically, quality is strongest when a brand enters in the growth phase. Third, Clements and Ohashi (2005) analyze the video game industry and comment on the importance of the network effect over the product generation: "*...the elasticity of demand for hardware [consoles] with respect to software variety is relatively low at the beginning of the product cycle*, *increases to a peak in the middle of the cycle*, *and then declines. This suggests that*, *while a low price is necessary to start the adoption process*, *software variety is necessary to continue adoption of the console* (p. 539)." Fourth, Klepper (1996) shows that firms have a greater incentive to invest in product innovation early in the PLC and process innovation later. Since the nature of quality improvement changes over the product generation, it follows that the effect of a quality improvement may change over the product generation. Fifth, in a modification of the Bass (1969) diffusion model incorporating indirect network effects, Chun and Hahn (2008) show the effect of indirect network effects on adoption rates changes as the level of product saturation changes. That is, saturation can be so great that the marginal benefit of increased network size is negligible. A Game Stop manager noted in our survey: "[in the mid-point of their life cycle] A wide variety of games makes the console seem like a better value." A Best Buy manager in our survey noted that toward the end of the life cycle, fewer games are slated as "most developers go to the next generation platform." Thus, it appears that different mechanisms may come into play as the product generation life cycle matures. Based on these discussions, we propose the following hypotheses:

**Hypothesis 1.** Both network and quality effects are factors that determine market share in high-tech networked markets (replication of Tellis, Yin, and Niraj (2009a)).

**Hypothesis 2.** Network and quality effects in a high-tech networked market vary over the product generation life cycle. Specifically, in the Growth and Maturity phases of the product generation life cycle, network effects can trump quality effects.

In the next section, we describe the data and the model.

## Empirical setting: the video game industry

Our key focus is to evaluate the quality and the network effects in a networked market over a product generation life cycle. For our empirical setting we chose the US video game industry for several reasons. First, it is widely recognized that network effects play an important role in market share outcomes in the home video game industry (see Clements and Ohashi 2005; Gretz 2010a; Gretz 2010b; Shankar and Bayus 2003; Zhu and Zhang 2010). Thus, it is a classic example of a high-tech networked market and allows us to replicate prior results. Second, Tellis, Yin, and Niraj (2009a) consider a market with indirect network effects, and accordingly, the video game industry satisfies that criterion. Third, a console with more compatible games is more attractive to consumers; a console with a larger installed base of consumers is more attractive to game makers. The existence of both the demand-side and the supply-side in our data allows us to overcome one of the key criticisms of Ratchford (2009): we are able to accommodate the supply-side equation in our estimation. Fourth, the data are provided by The NPD Group, a marketing research firm. Hence we did not have to collect any historical data, which eliminates missing data problems, along with those associated with inter-rater reliability.

Our empirical examination below considers whether the relative effects of quality and network size change over a console generation's life cycle. In the next section we describe the data, discuss our measure of console quality and network size, and consider different phases of the generation life cycle. The goal of the latter is to obtain an operational definition in order to classify consoles as they pass through particular phases of the generation life cycle. Later, we obtain quality and network size elasticity estimates for each phase.

### *Data*

The study employs a monthly data set covering January 1995 through October 2007. The data are provided by The NPD Group and include console and game point-of-sale data from approximately 65% of US game retailers. The data set contains observations on the quantity of consoles sold, average console price, the number of game titles available for a console in a month, and introduction and exit dates (where applicable).[2] It covers 15 consoles with 935 console/month observations in total. Next we discuss the various measures used in the analysis.

### *Measure of quality*

The quality variable is created from a hedonic equation where average console price is regressed on year/month interaction dummies and console dummies. Descriptive statistics and results for the hedonic estimation are shown in Tables 2 and 3, respectively.

The console dummy coefficients capture implicit price, or value, of unchanging console characteristics. We use these coefficients to construct our measure of console quality by adding the relevant coefficient to the constant (the constant serves as the quality measure for Sony PlayStation since that dummy was dropped from the regression to avoid perfect collinearity).[3] This results in a time-invariant summary quality variable for each console.

The hedonic approach is used to account for quality in many high-tech industries including video games (e.g. Gretz 2010b) and computers (e.g. Antonopoulos and Plutarchos 2011; Chun and Nadiri 2008; Filson 1998; Stavins 1997). This measure is objective and avoids missing data problems and potential issues associated with content analysis and subjectivity of raters. Also, results from the hedonic regression make sense on visual inspection. Table 4 displays correlations between the quality measure and various console characteristics: consoles with a higher summary quality value have greater graphics-processing ability, higher central processing unit (CPU) speed, more random access memory (RAM), can play games with more computer code (i.e. more intricate and graphically impressive games), are more likely to have the ability to play DVD movies, access the internet, and be backward compatible.

### *Measure of network*

We focus on the indirect network effect for our measure of network size. Consoles become more attractive as the number of available games for a console increases; the number of available games increases as the installed base for the console increases. Similar to Tellis, Yin, and Niraj (2009a), our measure of installed base is *cumulative console sales through the previous month*. For

[2] Throughout the analysis we adjust prices for inflation using the Consumer Price Index for All Urban Consumers (1982 – 1984 = 100) as the deflator. The data are available on the Bureau of Labor Statistics website: ftp://ftp.bls.gov/pub/special.requests/cpi/cpiai.txt.

[3] While not formally modeled, our underlying assumption is that consumers value various unchanging characteristics (e.g. central processing unit speed, random access memory, etc.) embodied in consoles. Given a budget constraint, consumers choose the console which maximizes utility; implicit prices therefore reflect the marginal value, or quality, of console characteristics.

Table 2
Summary statistics for hedonic regression. Nine hundred twenty four observations.

| | Mean | Std. dev. | Minimum | Maximum |
|---|---|---|---|---|
| Dependent variable | | | | |
| Natural log of inflation corrected average monthly console price | 4.091 | 0.760 | 0.728 | 5.689 |
| Dummy variables | | | | |
| 3DO | 0.047 | 0.211 | 0.000 | 1.000 |
| Sega Dreamcast | 0.051 | 0.220 | 0.000 | 1.000 |
| Nintendo Gamecube | 0.078 | 0.268 | 0.000 | 1.000 |
| Sega Genesis | 0.088 | 0.283 | 0.000 | 1.000 |
| Sega Genesis CDX | 0.055 | 0.228 | 0.000 | 1.000 |
| Atari Jaguar | 0.042 | 0.201 | 0.000 | 1.000 |
| Super Nintendo | 0.081 | 0.273 | 0.000 | 1.000 |
| Nintendo 64 | 0.111 | 0.315 | 0.000 | 1.000 |
| Sony PlayStation | 0.158 | 0.365 | 0.000 | 1.000 |
| Sony PlayStation 2 | 0.092 | 0.289 | 0.000 | 1.000 |
| Sony PlayStation 3 | 0.013 | 0.113 | 0.000 | 1.000 |
| Sega Saturn | 0.067 | 0.250 | 0.000 | 1.000 |
| Nintendo Wii | 0.013 | 0.113 | 0.000 | 1.000 |
| Microsoft Xbox | 0.078 | 0.268 | 0.000 | 1.000 |
| Microsoft Xbox 360 | 0.026 | 0.159 | 0.000 | 1.000 |

Summary statistics for month/year interaction dummies not displayed for brevity.

Table 3
Hedonic regression: price on console dummies and month/year interaction dummies.

| Variable | Coefficient | Standard error |
|---|---|---|
| Constant | 4.408*** | 0.105 |
| 3DO | −0.843*** | 0.067 |
| Sega Dreamcast | 0.102* | 0.061 |
| Nintendo Gamecube | 0.734*** | 0.054 |
| Sega Genesis | −1.319*** | 0.052 |
| Sega Genesis CDX | −0.905*** | 0.062 |
| Atari Jaguar | −1.408*** | 0.069 |
| Super Nintendo | −0.971*** | 0.054 |
| Nintendo 64 | −0.168*** | 0.045 |
| Sony PlayStation 2 | 1.116*** | 0.050 |
| Sony PlayStation 3 | 2.269*** | 0.114 |
| Sega Saturn | −0.556*** | 0.058 |
| Nintendo Wii | 1.460*** | 0.114 |
| Microsoft Xbox | 1.152*** | 0.054 |
| Microsoft Xbox 360 | 1.965*** | 0.084 |
| Number of observations | 924 | |
| $R^2$ | 0.830 | |
| Adjusted $R^2$ | 0.793 | |

* Significance at the 10% level.
*** Significance at the 1% level.
The dependent variable is the natural log of inflation corrected average monthly console price.
Console dummies included with Sony PlayStation as the base category.
Month/year interaction dummies included but not displayed for brevity.

Table 4
Correlations of quality measure with selected console characteristics.[a]

| Characteristic | Graphics processing speed | CPU | RAM | Game size | Disk | DVD | Internet | Backward compatible |
|---|---|---|---|---|---|---|---|---|
| Correlation | 0.901 | 0.792 | 0.769 | 0.669 | 0.591 | 0.751 | 0.861 | 0.611 |

[a] Characteristics for each console obtained from www.consoledatabase.com or manufacturers website when available.
CPU – central processing unit speed.
RAM – total random access memory contained in the console.
Game size – maximum program size of a game designed for the console.
Disk – dummy variable = 1 if the console uses disk based media.
DVD – dummy variable = 1 if the console can play DVD movies.
Internet – dummy variable = 1 if the console can access the internet and support on-line play.
Backward compatible – dummy variable = 1 if the console can play games designed for a previous generation console.

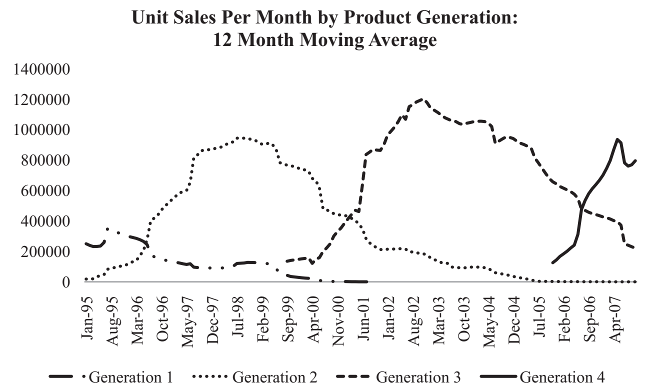


Fig. 1. Unit sales per month by product generation: 12 month moving average.

example, the installed base for a console in March 2002 would be cumulative sales through February 2002. The number of available games for a console is the number of games that achieved positive sales in a given month. In the empirical section below, we jointly estimate hardware demand via console utility (as a function of the number of available games, among other things) and the supply of the number of available games (as a function of the installed base, among other things). Other studies of the video game industry take this structural approach rather than using a reduced form approach (i.e., including the installed base directly in the hardware demand equation, thereby bypassing the number of available games equation) when estimating network effects on console demand (see, for example, Clements and Ohashi 2005; Gretz 2010b). In the next section we describe how we characterize the various stages of the generation life cycle.

### *The product generation life cycle for video game consoles*

There are 4 distinct product generations in our data delineated by dramatic improvements in hardware performance. Generation 1 includes 16-bit CPU systems, Sega Genesis and Super Nintendo. 32-bit and 64-bit CPU systems, 3DO, Jaguar, Nintendo 64, PlayStation, and Saturn, are included in Generation 2. Xbox, GameCube, Dreamcast, and PlayStation 2 are Generation 3 systems that use 128-bit processors. Finally, generation 4 systems Xbox 360, Nintendo Wii, and PlayStation 3 use multiple CPUs.

Fig. 1 displays the 12 month moving average (MMA) of console sales in each generation over the life of the data set. Notice console sales over the generation life cycle follow a pattern consistent with the product life cycle examined in Golder and Tellis (2004).[4] As such, we us Golder and Tellis (2004) to guide our delineation of different phases of the generation life cycle: Introduction, Growth, Maturity, and Decline.[5]

First, we define the Introduction phase of a generation as lasting from the first 6 months of generation sales until the monthly growth in the 12 MMA is greater than 20%. We do not consider increases over 20% in the first 6 months to indicate transition to the Growth stage because the sales base is so small. Second, we mark entry into the Maturity phase as the first of two consecutive months of less than 1% growth in the 12 MMA – this typically signals a leveling-off of generational sales. Third, we denote the beginning of the Decline phase when the 12 MMA decreases by more than 3% for two consecutive months – sales continually decrease until the generation exits the market. As a robustness check, we performed the empirical analysis below and varied the Introduction, Growth, Maturity, and Decline phases by 3 months over and under these operational definitions. Results are similar.

For visual inspection, we display the 12 MMA of generation sales as well as the transition points between different phases in the generation life cycle for generations 2 through 4 (generation 1 is always in decline) in Fig. 2a–c.

Tables 5a and 5b show the number of months each product generation and each console is observed in the different phases of the generation life cycle, respectively. From Table 5a, generation sales grow quickly, level off, then decline for the majority of the generation. Similarly, Table 5b shows consoles spend the longest time in the Decline phase and the shortest time in the Introduction and Growth phases while the greatest numbers of consoles are observed in the Maturity phase.

Table 6a shows descriptive statistics and Tables 6b and 6c show correlations for different variables in each phase of the generation life cycle (we provide definitions for the variables in the next section). In the next section, we determine if the relative effect on market share of console quality and network size (i.e. installed base), changes over the different stages.

## Results

The goal of this section is to jointly estimate console demand and the supply of the number of available games (Ratchford 2009), while allowing the effect of network and console quality to change over the generation life cycle (Rossi 2009). First, we discuss the hardware demand and software supply (number of available games) estimation equations, and then we present regression results and obtain elasticity estimates.

### *Hardware and software equations*

For hardware, we employ a standard logit model for aggregate data, where the dependent variable is the natural log of market share relative to the share of an outside good.[6] In developing

[4] Golder and Tellis (2004) also examine several problems associated with operationalizing the PLC. We refer the interested reader there for a detailed discussion.

[5] We use the MMA of sales to control for seasonal volatility (December sales are roughly 4 times higher than average monthly sales in the same year). Also, the 12 MMA produced clearer delineations of the different phases when compared to 3, 6, and 9 MMAs.

[6] See Appendix A for operational definitions of console share and share of the outside good.

Table 5a
Number of months console generation is observed in each phase of the product generation life cycle.

| | Months in introduction phase | Months in growth phase | Months in maturity phase | Months in decline phase |
|---|---|---|---|---|
| Generation 1 consoles | Not observed | Not observed | Not observed | 81 |
| Generation 2 consoles[a] | 16 | 18 | 20 | 101 |
| Generation 3 consoles[a] | 8 | 17 | 44 | 29 |
| Generation 4 consoles[a] | 7 | 12 | 5 | Not observed |
| Average (not observed = 0) | 7.750 | 11.750 | 17.250 | 52.750 |
| Average (independent of not observed) | 10.333 | 15.667 | 23.000 | 70.333 |

[a] Positive sales in the last month of the data set (October 2007).

Table 5b
Number of months console is observed in each phase of the product generation life cycle.

| | Months in introduction phase | Months in growth phase | Months in maturity phase | Months in decline phase |
|---|---|---|---|---|
| Genesis | Not observed | Not observed | Not observed | 81 |
| Super Nintendo | Not observed | Not observed | Not observed | 75 |
| Genesis CDX | Not observed | Not observed | Not observed | 51 |
| 3DO | 16 | 18 | 9 | Not observed |
| Jaguar | 16 | 18 | 5 | Not observed |
| Saturn | 11 | 18 | 20 | 13 |
| PlayStation[a] | 7 | 18 | 20 | 101 |
| Nintendo 64 | Not observed | 13 | 20 | 70 |
| Dreamcast | 8 | 17 | 21 | Not observed |
| PlayStation 2[a] | Not observed | 12 | 44 | 29 |
| GameCube[a] | Not observed | Not observed | 43 | 29 |
| Xbox[a] | Not observed | Not observed | 43 | 29 |
| Xbox 360[a] | 7 | 12 | 5 | Not observed |
| PlayStation 3[a] | Not observed | 7 | 5 | Not observed |
| Nintendo Wii[a] | Not observed | 7 | 5 | Not observed |
| Average (not observed = 0) | 4.333 | 9.333 | 16.000 | 31.867 |
| Average (independent of not observed) | 10.833 | 14.000 | 20.000 | 53.111 |

[a] Positive sales in the last month of the data set (October 2007).

the technique for estimating differentiated product discrete-choice demand models, Berry (1994) and Berry, Levinsohn, and Pakes (1995) show their model simplifies to the standard logit when consumer homogeneity is assumed (our assumption in this paper). This allows us to interpret the dependent variable as the mean utility of each product.[7] This is regressed on product characteristics (price, network size, and console quality) assumed to affect the utility consumers receive from a console. The hardware equation we estimate is:

$$\begin{aligned}\ln(\mathrm{Share}_t^k) - \ln(\mathrm{Share}_t^0) = {} & \delta_0 + \delta_p \mathrm{Price}_t^k + \delta_\theta^I \mathrm{Qual}^k + \delta_\theta^G \mathrm{Qual}^k \\ & + \delta_\theta^M \mathrm{Qual}^k + \delta_\theta^D \mathrm{Qual}^k + \delta_J^I \mathrm{Net}_t^k \\ & + \delta_J^G \mathrm{Net}_t^k + \delta_J^M \mathrm{Net}_t^k + \delta_J^D \mathrm{Net}_t^k \\ & + \delta_{\mathrm{Back}} \mathrm{Back}_t^k + \xi_t^k \end{aligned} \tag{1}$$

where $\mathrm{Share}_t^k$ is the market share of console $k$ at time $t$, $\mathrm{Share}_t^0$ is the market share of the outside option at time $t$, $\delta_0$ is a constant, $\mathrm{Price}_t^k$ is the price of console $k$ at time $t$, $\delta_p$ is the coefficient of price, $\mathrm{Qual}^k$ is console $k$'s quality, where $\delta_\theta^I$, $\delta_\theta^G$, $\delta_\theta^M$, and $\delta_\theta^D$ are the coefficients of console quality in the Introduction, Growth, Maturity, and Decline phase of the generation life cycle, respectively, $\mathrm{Net}_t^k$ is the indirect network effect – the number of available games – for console $k$ at time $t$, where $\delta_J^I$, $\delta_J^G$, $\delta_J^M$, and $\delta_J^D$ are the coefficients of the indirect network effect in the Introduction, Growth, Maturity, and Decline phase of the generation life cycle, respectively, and $\xi_t^k$ are unobserved characteristics of console $k$ at time $t$. It is important to note the coefficients on quality and network size are not directly comparable because the units of measure differ. In the next section we obtain elasticity estimates to aid in interpretation.

For software, Gretz (2010b), in a theoretical model of the video game console industry, shows the natural log of the number of available games is linearly related to the natural log of console quality and the natural log of a console's installed base of consumers. The latter captures the indirect network effect discussed above, while the former follows from a result that shows more games are available for higher quality consoles, ceteris paribus The resulting reduced-form model for the number

[7] A benefit of this specification is that it incorporates the effect of competing products' characteristics and prices on market share without having to include them directly in the estimation. We refer the reader to Berry (1994), Berry, Levinsohn, and Pakes (1995), and Nevo (2000) for the method of obtaining elasticities (own and cross) from estimates.

Table 6a
Descriptive statistics for variables of interest for different phases of the product generation life cycle.

| | Mean | Std. dev. | Minimum | Maximum |
|---|---|---|---|---|
| Introduction phase. 65 observations | | | | |
| Market share | 0.097 | 0.120 | 0.001 | 0.513 |
| Inflation corrected avg. console price[a,c] | 1.676 | 0.590 | 0.450 | 2.643 |
| Number of available games[a] | 0.942 | 1.210 | 0.050 | 4.460 |
| Number of available backward compatible games[a] | 0.426 | 1.237 | 0.000 | 4.060 |
| Installed base[b] | 36.989 | 43.168 | 0.000 | 168.240 |
| Backward compatible installed base[b] | 0.000 | 0.000 | 0.000 | 0.000 |
| Console quality | 3.983 | 0.984 | 2.999 | 6.373 |
| Growth phase. 140 observations | | | | |
| Market share | 0.203 | 0.184 | 0.000 | 0.604 |
| Inflation corrected avg. console price[a,c] | 1.158 | 0.624 | 0.203 | 2.955 |
| Number of available games[a] | 4.083 | 6.513 | 0.060 | 29.290 |
| Number of available backward compatible games[a] | 2.996 | 6.728 | 0.000 | 28.920 |
| Installed base[b] | 152.020 | 133.164 | 0.000 | 541.138 |
| Backward compatible installed base[b] | 0.000 | 0.000 | 0.000 | 0.000 |
| Console quality | 4.494 | 1.092 | 2.999 | 6.677 |
| Maturity phase. 240 observations | | | | |
| Market share | 0.255 | 0.193 | 0.000 | 0.641 |
| Inflation corrected avg. console price[a,c] | 0.848 | 0.452 | 0.107 | 2.743 |
| Number of available games[a] | 6.206 | 7.465 | 0.150 | 30.740 |
| Number of available backward compatible games[a] | 3.188 | 6.301 | 0.000 | 29.920 |
| Installed base[b] | 736.533 | 658.112 | 0.000 | 2840.000 |
| Backward compatible installed base[b] | 0.000 | 0.000 | 0.000 | 0.000 |
| Console quality | 4.956 | 0.770 | 2.999 | 6.677 |
| Decline phase. 478 Observations | | | | |
| Market share | 0.121 | 0.162 | 0.000 | 0.620 |
| Inflation corrected avg. console price[a,c] | 0.509 | 0.362 | 0.021 | 2.620 |
| Number of available games[a] | 5.795 | 5.804 | 0.500 | 27.610 |
| Number of available backward compatible games[a] | 1.477 | 3.607 | 0.000 | 13.530 |
| Installed base[b] | 1840.000 | 899.746 | 120.000 | 3880.000 |
| Backward compatible installed base[b] | 419.530 | 946.399 | 0.000 | 4070.000 |
| Console quality | 4.078 | 0.790 | 3.089 | 5.560 |

[a] Values divided by 100 for presentation purposes.
[b] Values divided by 10,000 for presentation purposes.
[c] Deflated using Consumer Price Index for All Urban Consumers (1980 − 1982 = 100).

Table 6b
Correlations for variables of interest for different phases of the product generation life cycle.

| | Market share | Inflation corrected avg. console price | Number of available games | Number of available backward compatible games | Installed base | Backward compatible installed base | Console quality |
|---|---|---|---|---|---|---|---|
| Introduction phase. 65 observations | | | | | | | |
| Market share | 1.000 | | | | | | |
| Inflation corrected avg. console price | 0.189 | 1.000 | | | | | |
| Number of available games | 0.581 | 0.170 | 1.000 | | | | |
| Number of available backward compatible games | 0.656 | 0.137 | 0.953 | 1.000 | | | |
| Installed base | 0.484 | −0.128 | 0.394 | 0.344 | 1.000 | | |
| Backward compatible installed base | | | | | | | |
| Console quality | 0.847 | 0.287 | 0.821 | 0.850 | 0.557 | | 1.000 |
| Growth phase. 140 observations | | | | | | | |
| Market share | 1.000 | | | | | | |
| Inflation corrected avg. console price | 0.407 | 1.000 | | | | | |
| Number of available games | 0.159 | 0.791 | 1.000 | | | | |
| Number of available backward compatible games | 0.161 | 0.790 | 0.994 | 1.000 | | | |
| Installed base | 0.534 | 0.227 | 0.048 | −0.001 | 1.000 | | |
| Backward compatible installed base | | | | | | | |
| Console quality | 0.529 | 0.847 | 0.712 | 0.704 | 0.493 | | 1.000 |

Table 6c
Correlations for variables of interest for different phases of the product generation life cycle.

| | Market share | Inflation corrected avg. console price | Number of available games | Number of available backward compatible games | Installed base | Backward compatible installed base | Console quality |
|---|---|---|---|---|---|---|---|
| Maturity phase. 240 observations | | | | | | | |
| Market share | 1.000 | | | | | | |
| Inflation corrected avg. console price | 0.385 | 1.000 | | | | | |
| Number of available games | 0.495 | 0.458 | 1.000 | | | | |
| Number of available backward compatible games | 0.384 | 0.577 | 0.958 | 1.000 | | | |
| Installed base | 0.681 | 0.049 | 0.696 | 0.493 | 1.000 | | |
| Backward compatible installed base | | | | | | | |
| Console quality | 0.379 | 0.713 | 0.549 | 0.545 | 0.334 | | 1.000 |
| Decline phase. 478 observations | | | | | | | |
| Market share | 1.000 | | | | | | |
| Inflation corrected avg. console price | 0.268 | 1.000 | | | | | |
| Number of available games | 0.453 | 0.290 | 1.000 | | | | |
| Number of available backward compatible games | 0.245 | 0.290 | 0.844 | 1.000 | | | |
| Installed base | 0.239 | −0.308 | 0.351 | 0.048 | 1.000 | | |
| Backward compatible installed base | −0.222 | −0.209 | −0.052 | −0.171 | 0.489 | 1.000 | |
| Console quality | 0.216 | 0.088 | 0.560 | 0.285 | 0.254 | 0.184 | 1.000 |

of available games (software supply) estimation is given by:

$$\begin{aligned}\ln(\mathrm{Net}_t^k) = {} & \phi_0 + \phi_\theta^I \ln(\mathrm{Qual}^k) + \phi_\theta^G \ln(\mathrm{Qual}^k) + \phi_\theta^M \ln(\mathrm{Qual}^k) \\ & + \phi_\theta^D \ln(\mathrm{Qual}^k) + \phi_{\mathrm{IB}}^I \ln(\mathrm{IB}_t^k) + \phi_{\mathrm{IB}}^G \ln(\mathrm{IB}_t^k) \\ & + \phi_{\mathrm{IB}}^M \ln(\mathrm{IB}_t^k) + \phi_{\mathrm{IB}}^D \ln(\mathrm{IB}_t^k) \\ & + \phi_{\mathrm{Back}} \ln\left(1 + \frac{\mathrm{Back\ IB}_t^k}{\mathrm{IB}_t^k}\right) + \eta_t^k \end{aligned} \tag{2}$$

where $\mathrm{Net}_t^k$ is the number of available games designed for console $k$ at time $t$, $\mathrm{IB}_t^k$ is the installed base of console $k$ at time $t$, $\mathrm{Qual}^k$ is the quality of console $k$, $\eta_t^k$ is a mean-zero error term, and the $\phi$'s are the parameters to be estimated.

Shankar, Carpenter, and Krishnamurthi (1999) capture various phases of the product life cycle by creating dummy variables for Growth and Maturity phases (see p. 270 equation (2)). In both Eqs. (1) and (2) we follow their strategy and allow the effects of console quality, the number of available games, and the installed base to vary over phases of the generation life cycle by interacting those measures with dummy variables which take the value 1 when the console is in a particular phase, 0 otherwise. Note this allows console quality to have different impacts over the life cycle, even though our quality measure is time-invariant for each console.

Several consoles are 'backward compatible' in that they can play games designed for a previous generation console(s). In Eq. (1) we include backward compatible games in our measure of the indirect network effect, $\mathrm{Net}_t^k$, by summing available game titles for the current generation and previously released game titles for the previous generation console(s) (see Ratchford 2009). For example, we include previously released PlayStation 2 game titles when calculating the number of available game titles for PlayStation 3 since the latter can play games designed for the former. To focus on the effect of current generation game titles, we include the number of backward compatible games, $\mathrm{Back}_t^k$, separately in the market share equation. Therefore, the coefficients on the indirect network effect, $\delta_J^I$, $\delta_J^G$, $\delta_J^M$, and $\delta_J^D$, capture the effect of current generation games in the specified phase of the generation life cycle. The sum of the coefficient on the indirect network effect in the specified phase of the generation life cycle and the coefficient on backward compatible games, $\delta_{\mathrm{Back}}$, will capture the effect of backward compatible games on market share. As such, we expect a negative coefficient on backward compatible games, $\delta_{\mathrm{Back}}$, since these games are likely to have a smaller effect on current generation market share than games designed for the current generation.[8] For example, a game designed for PlayStation 2 will have a smaller effect on the market share of PlayStation 3 than a game designed for PlayStation 3.

8 Note in Tables 6b and 6c there is a relatively high correlation between the Number of Available Games and the Number of Backward Compatible Games. Even though the correlation is high, we are not overly concerned with multicollinearity problems in the estimation because only 5 of the 15 consoles we examine are backward compatible. For non-backward compatible consoles the Number of Backward Compatible Games is always zero. This occurs 739 times out of 923 observations in our data set; enough to separately identify the effect of both backward compatible games and current generation games.

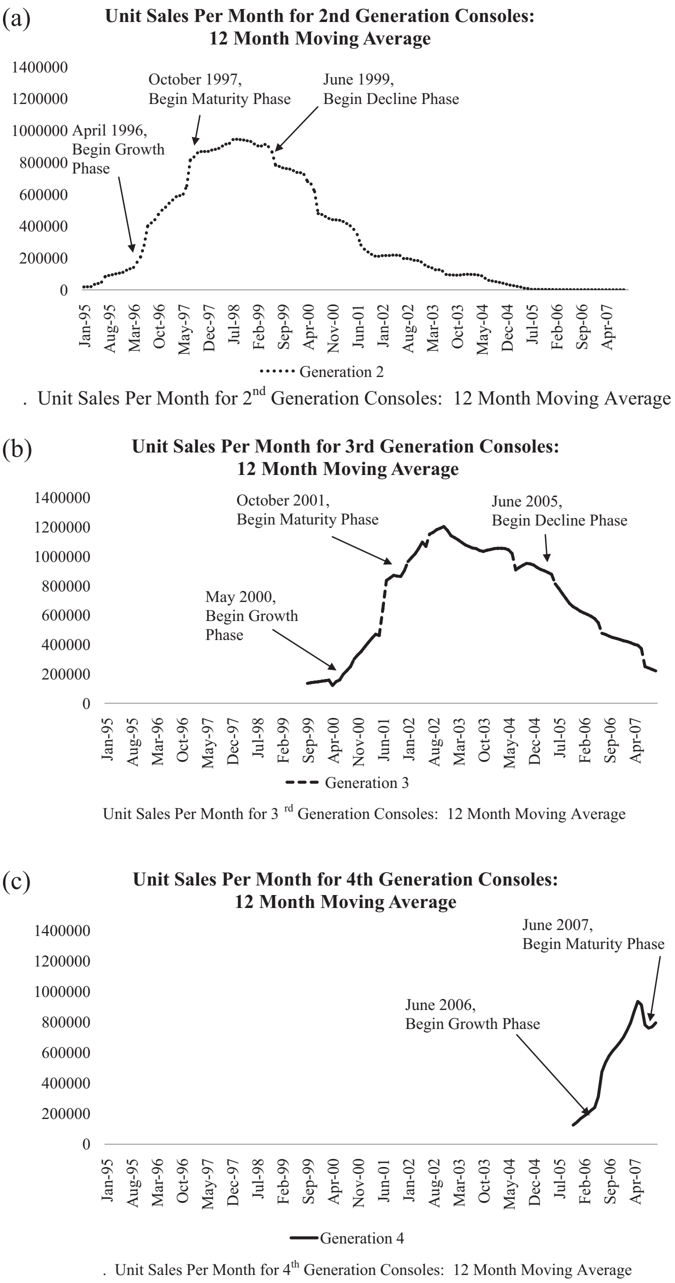


Fig. 2. (a) Unit sales per month for 2nd generation consoles: 12 month moving average. (b) Unit sales per month for 3rd generation consoles: 12 month moving average. (c) Unit sales per month for 4th generation consoles: 12 month moving average.

In Eq. (2) we accommodate backward compatibility by including all consoles that can play a particular game in the installed base calculations (see Ratchford 2009). For example, the installed base for the number of available PlayStation games includes PlayStation 2 purchasers because PlayStation games can be played on the PlayStation 2 console.[9] To focus on the effect of current generation installed base we include the natural log of 1 plus the fraction of the installed base that is backward compatible, $\ln(1 + (\text{Back IB}_t^k/\text{IB}_t^k))$, in the number of available games estimation.[10] Therefore, $\phi_{\text{IB}}^I$, $\phi_{\text{IB}}^G$, $\phi_{\text{IB}}^M$, and $\phi_{\text{IB}}^D$ capture the effect of the current generation installed base in a particular phase of the generation life cycle while the effect of another generation's installed base is a function of $\phi_{\text{Back}}$ and the appropriate $\phi_{\text{IB}}$ (depending on the phase of the generation life cycle).

Also, we use various cost side instruments (as suggested by Nevo 2000) to address endogeneity issues (Reibstein 2009; Rossi 2009) that arise in both Eqs. (1) and (2). Briefly, price is likely correlated with the error term in (1) because unobserved (to the econometrician) characteristics are taken into account by console firms when setting profit maximizing prices. The number of games may be correlated with the error term in (1) because they are likely influenced by the market share of new consumers (Zhu and Zhang 2010). The installed base in (2) is likely correlated with the error term because unobserved shocks in the software market in the previous period can produce an increase in the current period's installed base (Clements and Ohashi 2005). Appendix B discusses and describes the instruments.

Finally, though not displayed in Eq. (1) or (2), we include a number of control variables. First, we include month and year dummies in both estimations to control for any industry-wide dynamics or systematic trends. Second, we include the ages of the phases of the generation life cycle to control for endogeneity associated with how we define the different phases of the generation life cycle.[11] For example, the Decline phase of the generation life cycle is characterized by continually decreasing market share until the console exits the market. Third, we include console age (1 in the first month, 2 in the second, and so on), either by itself or interacted with phase dummies when it increases explanatory power, to help control for market share changes over the generation life cycle predicted by classic diffusion models (e.g. Bass 1969). We now turn to the estimation results.

## *Estimation results*

Descriptive statistics for the hardware demand estimations and number of available games estimations are displayed in Tables 7 and 8, respectively. We consider hardware first; estimates are displayed in Table 9. As a benchmark, we include estimations (1), (3), and (5) (and estimations (7), (9), and (11) in software estimations) which do not incorporate any generation life cycle interaction effects. In contrast, estimations (2), (4), and (6) (and estimations (8), (10), and (12) in the software

[9] We also tried using the natural log of the current generation installed base (not including backward compatible installed base) interacted with the generation life cycle dummies. Results are similar to those presented below.

[10] We add 1 to the fraction of the installed base that is backward compatible before taking the natural log to avoid undefined values for consoles that are not backward compatible. That is, $\text{Back IB}_t^k/\text{IB}_t^k = 0$ for consoles not backward compatible; the natural log of which is undefined. Adding 1 avoids this complication; $\ln(1 + (\text{Back IB}_t^k/\text{IB}_t^k)) = 0$ when consoles are not backward compatible and $\ln(1 + (\text{Back IB}_t^k/\text{IB}_t^k)) > 0$ when consoles are backward compatible.

[11] These are four variables (one for each phase) which take the value 0 when the console is not in the particular phase, 1 when the console is in the first month of the phase, 2 in the second month, and so on.

Table 7
Descriptive statistics for hardware demand estimations. Nine hundred twenty three observations.

| Dependent variable | Mean | Std. dev. | Min. | Max. |
|---|---|---|---|---|
| $\ln(s_t^k) - \ln(s_t^0)$ | −7.477 | 3.250 | −16.875 | −2.145 |
| Product lifecycle dummies | | | | |
| Introduction | 0.070 | 0.256 | 0.000 | 1.000 |
| Growth | 0.152 | 0.359 | 0.000 | 1.000 |
| Maturity | 0.260 | 0.439 | 0.000 | 1.000 |
| Decline | 0.518 | 0.500 | 0.000 | 1.000 |
| Endogenous regressors[a] | | | | |
| Inflation corrected avg. console price | 0.778 | 0.567 | 0.021 | 2.955 |
| Number of available games × introduction | 0.066 | 0.400 | 0.000 | 4.460 |
| Number of available games × growth | 0.619 | 2.923 | 0.000 | 29.290 |
| Number of available games × maturity | 1.614 | 4.676 | 0.000 | 30.740 |
| Number of available games × decline | 3.001 | 5.081 | 0.000 | 27.610 |
| Number of backward compatible games | 2.079 | 4.978 | 0.000 | 29.920 |
| Exogenous regressors | | | | |
| Console quality × introduction | 0.281 | 1.052 | 0.000 | 6.373 |
| Console quality × growth | 0.682 | 1.668 | 0.000 | 6.677 |
| Console quality × maturity | 1.289 | 2.210 | 0.000 | 6.677 |
| Console quality × decline | 2.112 | 2.116 | 0.000 | 5.560 |
| Instruments[a] | | | | |
| Electronic Computer Manufacturing PPI (ECM) | 2.273 | 1.339 | 0.666 | 5.401 |
| Computer Storage Device Manufacturing PPI (CSDM) | 1.873 | 0.810 | 0.872 | 3.590 |
| Audio and Video Equipment Manufacturing PPI (AVEM) | 0.755 | 0.053 | 0.641 | 0.841 |
| Magnetic and Optical Recording Media Manufacturing PPI (MORMM) | 0.754 | 0.053 | 0.650 | 0.848 |
| MORMM × Introduction[b] | 0.057 | 0.206 | 0.000 | 0.848 |
| MORMM × Growth[b] | 0.116 | 0.276 | 0.000 | 0.814 |
| MORMM × Maturity[b] | 0.193 | 0.326 | 0.000 | 0.801 |
| Game Software Publishing PPI (GSP) | 0.445 | 0.339 | 0.000 | 1.033 |
| GSP × Introduction[b] | 0.010 | 0.081 | 0.000 | 0.848 |
| GSP × Growth[b] | 0.034 | 0.141 | 0.000 | 0.777 |
| GSP × Maturity[b] | 0.154 | 0.295 | 0.000 | 1.033 |
| Average game age (GA) × Console Age (CA) × AVEM | 1463.114 | 1790.288 | 0.000 | 8502.030 |
| GA × CA × MORMM | 1462.414 | 1790.407 | 0.000 | 8479.175 |
| GA × CA × GSP | 1068.306 | 1698.807 | 0.000 | 8284.908 |

[a] Values divided by 100 for presentation purposes.
[b] Instruments interacted with product lifecycle dummies used in addition to all other instruments in hardware estimations (4) and (6) in Table 9.

Table 8
Descriptive statistics for number of available games estimations. Nine hundred thirteen observations.

| | Mean | Std. dev. | Min. | Max. |
|---|---|---|---|---|
| Dependent variable | | | | |
| LN(number of available games) | 5.295 | 1.091 | 1.609 | 7.250 |
| Endogenous regressors | | | | |
| LN(installed base) × Introduction | 0.830 | 3.114 | 0.000 | 14.336 |
| LN(installed base) × Growth | 2.049 | 4.919 | 0.000 | 15.504 |
| LN(installed base) × Maturity | 4.002 | 6.768 | 0.000 | 17.163 |
| LN(installed base) × Decline | 8.670 | 8.313 | 0.000 | 18.076 |
| LN(1 + backward compatible installed base/installed base) | 0.041 | 0.102 | 0.000 | 0.454 |
| Exogenous regressors | | | | |
| LN(console quality) × Introduction | 0.090 | 0.340 | 0.000 | 1.852 |
| LN(console quality) × Growth | 0.219 | 0.531 | 0.000 | 1.899 |
| LN(console quality) × Maturity | 0.414 | 0.702 | 0.000 | 1.899 |
| LN(console quality) × Decline | 0.726 | 0.707 | 0.000 | 1.716 |
| Instruments[a] | | | | |
| Magnetic and Optical Recording Media Manufacturing PPI (MORMM) | 0.754 | 0.053 | 0.650 | 0.848 |
| MORMM × Introduction[b] | 0.054 | 0.201 | 0.000 | 0.848 |
| MORMM × Growth[b] | 0.114 | 0.274 | 0.000 | 0.814 |
| MORMM × Maturity[b] | 0.193 | 0.326 | 0.000 | 0.801 |
| Game Software Publishing PPI (GSP) | 0.445 | 0.339 | 0.000 | 1.033 |
| Consumer Price Index (CPI) | 1.756 | 0.168 | 1.503 | 2.089 |
| Average game age (GA) × console age (CA) × MORMM | 1478.431 | 1793.600 | 0.903 | 8479.175 |

[a] Values divided by 100 for presentation purposes.
[b] Instruments interacted with product lifecycle dummies used in addition to all other instruments in hardware estimations (10) and (12) in Table 10.

Table 9
Mean console utility estimations: natural log of console share subtracted from natural log of outside option share on explanatory variables.

| | OLS estimations | | 2SLS estimations | | GMM estimations | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5)[a] | (6)[b] |
| Inflation corrected avg. console price | 0.820*** | 0.889*** | −0.518 | −1.632 | −1.038 | −2.510* |
| | (0.276) | (0.295) | (1.203) | (1.406) | (1.561) | (1.370) |
| Number of available games | 0.340*** | | 0.403*** | | 0.384*** | |
| | (0.029) | | (0.084) | | (0.104) | |
| Number of available games × Introduction | | −0.045 | | 1.427*** | | 1.112*** |
| | | (0.206) | | (0.429) | | (0.319) |
| Number of available games × Growth | | 0.502*** | | 1.505*** | | 1.425*** |
| | | (0.077) | | (0.242) | | (0.243) |
| Number of available games × Maturity | | 0.529*** | | 1.545*** | | 1.456*** |
| | | (0.069) | | (0.196) | | (0.192) |
| Number of available games × Decline | | 0.422*** | | 0.582*** | | 0.500*** |
| | | (0.051) | | (0.118) | | (0.112) |
| Number of backward compatible games | −0.466*** | −0.650*** | −0.264 | −1.137*** | −0.142 | −1.000*** |
| | (0.042) | (0.076) | (0.185) | (0.267) | (0.215) | (0.268) |
| Console quality | 5.514*** | | 4.697*** | | 4.558*** | |
| | (0.330) | | (1.226) | | (1.472) | |
| Console quality × Introduction | | 4.945*** | | 2.921** | | 4.051*** |
| | | (0.443) | | (1.273) | | (1.115) |
| Console quality × Growth | | 5.148*** | | 2.695** | | 3.698*** |
| | | (0.383) | | (1.071) | | (0.944) |
| Console quality × Maturity | | 5.017*** | | 2.572** | | 3.469*** |
| | | (0.355) | | (1.041) | | (0.916) |
| Console quality × Decline | | 4.937*** | | 3.103*** | | 4.098*** |
| | | (0.391) | | (1.058) | | (0.916) |
| Number of observations | 923 | 923 | 923 | 923 | 913 | 913 |
| $R^2$ | 0.634 | 0.657 | | | | |
| *J* statistic | | | 8.945 | 11.105 | 9.847 | 13.554 |
| 1-stg *F*-stats | | | | | | |
| Inflation corrected avg. console price | | | 43.89*** | 8.78*** | | |
| Number of available games | | | 15.46*** | | | |
| Number of available games × Introduction | | | | 48.63*** | | |
| Number of available games × Growth | | | | 6.63*** | | |
| Number of available games × Maturity | | | | 7.30*** | | |
| Number of available games × Decline | | | | 12.65*** | | |
| Number of backward compatible games | | | 4.54*** | 6.54*** | | |

[a] Estimated jointly with number of available games equation (estimation (11) in Table 10).
[b] Estimated jointly with number of available games equation (estimation (12) in Table 10).
Dependent variable: The natural log of console share subtracted from the natural log of outside option share.
A constant, year and month dummies, generation phase age, and console age are included in estimations but not displayed for brevity.
Instruments for 2SLS and GMM estimations are listed in Table 7.
* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.
Heteroskedastic consistent standard errors are presented in parenthesis.

estimations) incorporate all interaction effects displayed in Eq. (1) (and Eq. (2) for software estimation).

Table 9 displays Ordinary Least Squares (OLS), 2-Stage Least Squares (2SLS), and joint Generalized Method of Moments (GMM) parameter estimates for hardware. Below we discuss estimates for software (results are displayed in Table 10). However, while we do not impose cross equation restrictions, joint estimation improves efficiency if errors from both equations are correlated. Therefore, hardware demand and software availability are jointly estimated to obtain the joint GMM results (estimations (5) and (6)). OLS and 2SLS results (estimations (1)–(4)) are for hardware, separate from software variety. We provide OLS and 2SLS results for comparison, however Appendix C discusses why the joint GMM estimation is preferred. As such, we consider results from the GMM estimations below.

First, note that consistent with the findings of Tellis, Yin, and Niraj (2009a), estimations (5) and (6) show that both quality and network effects have a significant effect on mean console utility and, as a result, influence market share. Thus, we are able to successfully replicate prior research and find support for Hypothesis 1. However, estimation (6) has significantly more explanatory power than estimation (5). That is, we can reject several hypotheses concerning statistically similar effects of console quality interacted with the generation life cycle dummies and parallel hypotheses concerning the effect of the number of available

Table 10
Number of available games estimations: natural log of number of available games on explanatory variables.

| | OLS estimations | | 2SLS estimations | | GMM estimations | |
|---|---|---|---|---|---|---|
| | (7) | (8) | (9) | (10) | (11)[a] | (12)[b] |
| LN(installed base) | 0.557*** | | 1.536*** | | 1.577*** | |
| | (0.033) | | (0.307) | | (0.245) | |
| LN(installed base) × Introduction | | 0.685*** | | 1.168*** | | 1.301*** |
| | | (0.038) | | (0.185) | | (0.200) |
| LN(installed base) × Growth | | 0.524*** | | 0.993*** | | 1.086*** |
| | | (0.056) | | (0.192) | | (0.208) |
| LN(installed base) × Maturity | | 0.410*** | | 0.983*** | | 1.080*** |
| | | (0.053) | | (0.229) | | (0.247) |
| LN(installed base) × Decline | | 0.474*** | | 0.934*** | | 1.012*** |
| | | (0.030) | | (0.115) | | (0.123) |
| LN(1 + Backward compatible installed base/installed base) | −0.067 | 3.567*** | −18.266 | −1.571 | −12.986 | −3.044 |
| | (0.858) | (0.158) | (22.532) | (5.962) | (17.650) | (6.529) |
| LN(console quality) | 1.535*** | | −4.670 | | −6.395 | |
| | (0.452) | | (8.388) | | (6.617) | |
| LN(console quality) × Introduction | | 1.920*** | | −0.623 | | −1.176 |
| | | (0.325) | | (0.766) | | (0.815) |
| LN(console quality) × Growth | | 3.241*** | | 0.224 | | −0.176 |
| | | (0.528) | | (1.018) | | (1.085) |
| LN(console quality) × Maturity | | 4.030*** | | −0.042 | | −0.512 |
| | | (0.507) | | (1.328) | | (1.418) |
| LN(console quality) × Decline | | 4.720*** | | 1.369** | | 1.011* |
| | | (0.348) | | (0.581) | | (0.612) |
| Number of observations | 913 | 913 | 913 | 913 | 913 | 913 |
| $R^2$ | 0.603 | 0.879 | | | | |
| *J* statistic | | | 0.512 | 1.525 | 9.847 | 13.554 |
| 1-stg *F*-stats | | | | | | |
| LN(installed base) | | | 75.89*** | | | |
| LN(installed base) × Introduction | | | | 64.96*** | | |
| LN(installed base) × Growth | | | | 50.29*** | | |
| LN(installed base) × Maturity | | | | 28.19*** | | |
| LN(installed base) × Decline | | | | 634.71*** | | |
| LN(1 + Backward compatible installed base/installed base) | | | 0.67 | 2.90*** | | |

[a] Estimated jointly with console utility equation (estimation (5) in Table 9).
[b] Estimated jointly with console utility equation (estimation (6) in Table 9).
Dependent variable: The natural log of the number of available games.
A constant, year and month dummies, generation phase age, and console age interacted with generation dummies are included in estimations but not displayed for brevity.
Instruments for 2SLS and GMM estimations are listed in Table 8.
* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.
Heteroskedastic consistent standard errors are presented in parenthesis.

games.[12] Thus, network and quality effects vary over the generation life cycle. Therefore, we find support for Hypothesis 2.

Further, it should be noted that failure to take into account phases of the generation life cycle may bias results. Relative to estimation (6), we find estimation (5) implies a weaker effect for the number of available games, a stronger effect for console quality, and a statistically similar effect of backward compatible games and current generation games on console utility (the number of backward compatible games is not negative and significant).

Second, focusing on estimation (6), parameter estimates by and large conform to priors: price has a negative (though weakly significant) effect on utility, backward compatible games have a significantly smaller effect on utility than current generation

[12] We test a number of different possibilities for statistically similar coefficients using standard Wald test methodology. First consider console quality: restricting the coefficients for console quality interacted with Introduction and Growth dummies, Growth and Maturity dummies, Maturity and Decline dummies, and all dummies yields $\chi^2$ statistics (with degrees of freedom in parenthesis) 2.16 (1), 1.39 (1), 8.78 (1), and 11.05 (3). The associated *p*-values are 0.142, 0.238, 0.003, and 0.011, respectively. Second consider the number of available games: restricting the coefficients for the number of available games interacted with Introduction and Growth dummies, Growth and Maturity dummies, Maturity and Decline dummies, and all dummies yields $\chi^2$ statistics 0.88 (1), 0.06 (1), 31.76 (1), and 33.95 (3). The associated *p*-values are 0.348, 0.805, <0.000, and <0.000, respectively. Finally, restricting console quality to have the same effect throughout the generation life cycle while simultaneously restricting the number of available games to have the same effect throughout the generation life cycle yields a $\chi^2$ statistic of 48.08 (6) with an associated *p*-value <0.000.

games,[13] and console quality and the number of available games have a positive and significant effect in each phase of the generation life cycle. Interestingly, the number of available games has the smallest positive effect on market share in the Decline phase of the product generation. It is possible consumers have reached the point of saturation (Chun and Hahn 2008). Any increase in available games beyond some threshold level may have a much smaller effect on market share. In the words of one retail manager (Best Buy): "game developers do not slate any new games [at the end of the life cycle]" as "most developers go to the next generation platform."

Third, the effect of console quality appears to be strongest in the Introduction and Decline phases and weakest in the Growth and Maturity phases; quality is more important at the beginning and end of the generation life cycle compared to the middle. The number of available games follows the opposite pattern. This suggests there may be conditions over the generation life cycle where the network effect is stronger than the quality effect. This result suggests some support for Hypothesis 2. However, we urge caution in directly comparing coefficients on the number of available games and console quality. First, as stated above, quality may also influence market share indirectly through the number of available games. Second, a direct comparison will be misleading because the units of measure differ (Rossi 2009). After we consider the number of available game estimations, we facilitate comparison by obtaining market share elasticities to both console quality and network size; this normalizes the units of measure and allows a direct comparison (Rossi 2009).

Table 10 displays results for the software estimations. We refer to the GMM estimations for our discussion below because evidence suggests the OLS estimate is biased (the Hausman (1978) statistic is significant) while the instruments are strong (again, see Appendix C for a more detailed explanation of why GMM is preferred). It should be noted OLS and 2SLS results are for game availability, separate from hardware demand. However, software is jointly estimated with hardware to obtain joint GMM results. Specifically, estimations (11) and (12) are the software portions of estimations (5) and (6) in Table 9, respectively.

Note the coefficients in Table 10 are elasticity estimates given the log–log specification; direct comparison between the effect of console quality and the installed base on the number of available games can be made without adjustment. However, we focus on how the effect of each variable changes over the generation life cycle before comparison.

As with results from the console utility estimations, including console quality and the installed base interacted with generation life cycle dummies significantly increases the explanatory power of the estimations. We reject several hypotheses concerning statistically similar effects of console quality interacted with the generation life cycle dummies and parallel hypotheses concerning the effect of the installed base interacted with generation life cycle dummies.[14] Again, similar to the console utility estimations, not taking phases of the generation life cycle into account may bias results. Comparing results from estimations (11) and (12), we find estimation (11) overstates of the effect of installed base and understates the effect of console quality (console quality is negative and insignificant) on the number of available games.

Note in (12) the effect of the installed base on the number of available games is strongest in the Introduction phase and weakest in the Decline phase. However, the opposite is true for console quality: the effect of console quality is only significant in the Decline phase of the generation life cycle. This echoes results from the console utility estimations where the effect of console quality and the network effect may be stronger at different points over the generation life cycle. This suggests there may be conditions where the quality effect is not dominant (i.e. the network effect is relatively strong while the quality effect is relatively weak). In the next section, we obtain elasticities for hardware demand and incorporate elasticities for the number of available games to directly compare the network effect and quality effect on market share over the generation life cycle.

*Comparison of the quality effect and network effect over the product life cycle*

Elasticities aid in direct comparison of the quality and network effect (Rossi 2009). Specifically, we define market share elasticity with respect to console quality directly through the hardware estimation as $\varepsilon^{\text{Direct}}_{\text{Share,Quality}} = (\%\Delta\,\text{Market Share}/\%\Delta\,\text{Console Quality})$. However, console quality affects market share in two ways: (1) directly in the hardware demand equation and (2) indirectly through the number of available games equation. With respect to the latter, a

[13] Recall from the discussion of Eq. (1) above, the effect of backward compatible games in each phase of the generation life cycle is obtained by summing the number of backward compatible games coefficient and the number of available games coefficient for the specific phase. The negative sign on the number of backward compatible games coefficient implies these games have a smaller effect than current generation games. We note, however, there is an interesting result that provides an avenue for future research; we find a negative (and significant at the 99% level using a *t*-test) effect of backward compatible games when summing the coefficients in the Decline phase.

[14] First consider console quality: restricting the coefficients for console quality interacted with Introduction and Growth dummies, Growth and Maturity dummies, Maturity and Decline dummies, and all dummies yields $\chi^2$ statistics (with degrees of freedom in parenthesis) 1.35 (1), 0.10 (1), 2.19 (1), and 17.03 (3). The associated *p*-values are 0.245, 0.758, 0.139, and 0.001, respectively. It should be noted restrictions on the console quality coefficients are only significant at the 15% level when comparing the Maturity phase to the Decline phase. However, simultaneously restricting console quality to have the same effect throughout the generation lifecycle is significant at the 1% level. Second consider the installed base: restricting the coefficients for the installed base interacted with Introduction and Growth dummies, Growth and Maturity dummies, Maturity and Decline dummies, and all dummies yields $\chi^2$statistics 4.29 (1), 0.002 (1), 0.21 (1), and 12.41 (3). The associated *p*-values are 0.038, 0.962, 0.643, and 0.006, respectively. As with the quality restrictions, the individual restrictions on installed base are only significant once, when comparing the Introduction phase to the Growth phase, at the 5% level. However, simultaneously restricting installed base to have the same effect throughout the generation life cycle is significant at the 1% level. Finally, restricting console quality to have the same effect throughout the generation life cycle while simultaneously restricting the installed base to have the same effect throughout the generation life cycle yields a $\chi^2$ statistic of 89.63 (6) with an associated *p*-value <0.000.

Table 11
Elasticity estimates over the generation life cycle. Elasticities calculated at average variable values.

| | Introduction | Growth | Maturity | Decline | Benchmark |
|---|---|---|---|---|---|
| Number of observations | 65 | 140 | 240 | 478 | 923 |
| Direct elasticities | | | | | |
| $\varepsilon_{\text{Share,Games}}$ | 0.945 | 4.639 | 6.733 | 2.544 | 1.698 |
| $\varepsilon^{\text{Direct}}_{\text{Share,Quality}}$ | 14.571 | 13.248 | 12.809 | 14.680 | 16.568 |
| $\varepsilon_{\text{Games,IB}}$ | 1.301 | 1.086 | 1.080 | 1.012 | 1.577 |
| $\varepsilon_{\text{Games,Quality}}$ | NS* | NS* | NS* | 1.011 | NS* |
| Indirect elasticities | | | | | |
| $\varepsilon^{\text{Indirect}}_{\text{Share,IB}} = \varepsilon_{\text{Share,Games}} \times \varepsilon_{\text{Games,IB}}$ | 1.229 | 5.040 | 7.273 | 2.575 | 2.677 |
| $\varepsilon^{\text{Indirect}}_{\text{Share,Quality}} = \varepsilon_{\text{Share,Games}} \times \varepsilon_{\text{Games,Quality}}$ | NS* | NS* | NS* | 2.572 | NS* |
| Total elasticities | | | | | |
| Installed base elasticity, $\varepsilon^{\text{Total}}_{\text{Share,IB}} = \varepsilon^{\text{Indirect}}_{\text{Share,IB}}$ | 1.229 | 5.040 | 7.273 | 2.575 | 2.677 |
| Console quality elasticity, $\varepsilon^{\text{Total}}_{\text{Share,Quality}} = \varepsilon^{\text{Direct}}_{\text{Share,Quality}} + \varepsilon^{\text{Indirect}}_{\text{Share,Quality}}$ | 14.571 | 13.248 | 12.809 | 17.252 | 16.568 |
| Weighted average installed base elasticity[a] | | | | 4.076 | 2.677 |
| Weighted average console quality elasticity[a] | | | | 15.301 | 16.568 |

Elasticities for Introduction, Growth, Maturity, and Decline are calculated using coefficients from estimations (6) and (12) while elasticities for Benchmark are calculated using coefficients from estimations (5) and (11).

[a] Benchmark elasticities are not weighted. Elasticities incorporating generation life cycle considerations are weighted by the number of observations in the phase of generation life cycle. An elasticity of 0 is used when the observed elasticity is not significant.

* Regression coefficients used in determining elasticities are not statistically significant at the 10% level. NS = not significant.

change in console quality will change the number of available games, which affects market share. We obtain the indirect effect of console quality on market share using the chain formula:

$$\varepsilon^{\text{Indirect}}_{\text{Share,Quality}} = \frac{\%\Delta\,\text{Market Share}}{\%\Delta\,\text{Games}} \times \frac{\%\Delta\,\text{Games}}{\%\Delta\,\text{Console Quality}} = \varepsilon_{\text{Share,Games}} \times \varepsilon_{\text{Games,Quality}}.$$

The total elasticity of market share with respect to console quality is found by simply summing the direct and indirect effect, $\varepsilon^{\text{Total}}_{\text{Share,Quality}} = \varepsilon^{\text{Direct}}_{\text{Share,Quality}} + \varepsilon^{\text{Indirect}}_{\text{Share,Quality}}$. Installed base only affects market share indirectly through the number of available games. We define the total elasticity of market share with respect to the installed base as:

$$\varepsilon^{\text{Total}}_{\text{Share,IB}} = \varepsilon^{\text{Indirect}}_{\text{Share,IB}} = \frac{\%\Delta\,\text{Market Share}}{\%\Delta\,\text{Games}} \times \frac{\%\Delta\,\text{Games}}{\%\Delta\,\text{Installed Base}} = \varepsilon_{\text{Share,Games}} \times \varepsilon_{\text{Games,IB}}.$$

As stated above, the coefficients from the number of available game estimations are elasticities because of the log–log specification. However, this does not apply in the hardware estimations. With a logit demand structure (see Zhu and Zhang 2010 for a recent application in the marketing literature) the elasticity of any variable with respect to market share is given by $\delta_x x(1-s)$, where $\delta_x$ is the coefficient on $x$ from the hardware estimation, $x$ is the value of the variable, and $s$ is the market share. Notice this formulation allows elasticity to change as the values of $x$ and $s$ change. In Table 11 we present elasticities calculated at average variable values for two cases: one where elasticities change over the generation life cycle (calculated using coefficients from estimations (6) and (12)) and a benchmark case where elasticities are held constant over the generation life cycle (calculated using coefficients from estimations (5) and (11)).

Looking at the elasticities from the benchmark case as well as the weighted average elasticities from the generation life cycle case, results appear to support previous findings in the literature. Tellis, Yin, and Niraj (2009a) find quality often trumps network size in their examination of 19 industries. Gretz (2010b) finds similar results looking specifically at the video game industry. *On average*, market share is more sensitive to quality than network size. This general finding supports the results of Tellis, Yin, and Niraj (2009a). Note, however, even though both elasticity estimates give the same result, the quality advantage is overstated when the benchmark case is compared to the generational life cycle case. Also, the benchmark case does not show how the relative effects can change over the generation life cycle.

Focusing on the generation life cycle case, the relative impact of quality over network size becomes weaker from Introduction through Maturity and stronger in Decline. While the console quality effect is roughly 11.9 (≈14.571/1.229) times the network size effect in the Introduction phase, the advantage decreases to 2.6 (≈13.248/5.040) in the Growth phase, falls further to 1.76 (≈12.809/7.273) in the Maturity phase, but jumps up to 6.7 (≈17.252/2.575) in the Decline phase. In this example, the quality effect is always stronger than the network size effect in all phases of the generation life cycle, but this relationship changes drastically at different variable values. For example, consider Table 12.

Table 12 displays elasticities calculated with a one standard deviation increase in console quality and the number of available games. First, the benchmark case shows *on average* the quality effect still dominates. However, it overstates the quality versus network advantage when compared to the generation life cycle case. Second, the quality advantage drops when comparing Tables 11 and 12. Looking at the weighted average elasticities for the generational life cycle case, at average values the quality advantage is 3.75 (≈15.301/4.076); with a one standard deviation increase this advantage falls to 2.15 (≈19.367/9.017).

Table 12
Elasticity estimates over the generation life cycle. Elasticities calculated at average variable values plus a one standard deviation increase in number of available games and console quality.

| | Introduction | Growth | Maturity | Decline | Benchmark |
|---|---|---|---|---|---|
| Number of observations | 65 | 140 | 240 | 478 | 923 |
| Direct elasticities | | | | | |
| $\varepsilon_{Share,Games}$ | 2.160 | 12.039 | 14.831 | 5.091 | 3.731 |
| $\varepsilon^{Direct}_{Share,Quality}$ | 18.169 | 16.468 | 14.799 | 17.523 | 20.111 |
| $\varepsilon_{Games,IB}$ | 1.301 | 1.086 | 1.080 | 1.012 | 1.577 |
| $\varepsilon_{Games,Quality}$ | NS* | NS* | NS* | 1.011 | NS* |
| Indirect elasticities | | | | | |
| $\varepsilon^{\mathrm{Indirect}}_{\mathrm{Share,IB}} = \varepsilon_{\mathrm{Share,Games}} \times \varepsilon_{\mathrm{Games,IB}}$ | 2.809 | 13.080 | 16.021 | 5.154 | 5.882 |
| $\varepsilon^{\mathrm{Indirect}}_{\mathrm{Share,Quality}} = \varepsilon_{\mathrm{Share,Games}} \times \varepsilon_{\mathrm{Games,Quality}}$ | NS* | NS* | NS* | 5.148 | NS* |
| Total elasticities | | | | | |
| Installed base elasticity, $\varepsilon^{\mathrm{Total}}_{\mathrm{Share,IB}} = \varepsilon^{\mathrm{Indirect}}_{\mathrm{Share,IB}}$ | 2.809 | 13.080 | 16.021 | 5.154 | 5.882 |
| Console quality elasticity, $\varepsilon^{\mathrm{Total}}_{\mathrm{Share,Quality}} = \varepsilon^{\mathrm{Direct}}_{\mathrm{Share,Quality}} + \varepsilon^{\mathrm{Indirect}}_{\mathrm{Share,Quality}}$ | 18.169 | 16.468 | 14.799 | 22.672 | 20.111 |
| Weighted average installed base elasticity[a] | | | | 9.017 | 5.882 |
| Weighted average console quality elasticity[a] | | | | 19.367 | 20.111 |

Elasticities for Introduction, Growth, Maturity, and Decline are calculated using coefficients from estimations (6) and (12) while elasticities for Benchmark are calculated using coefficients from estimations (5) and (11).

[a] Benchmark elasticities are not weighted. Elasticities incorporating generation life cycle considerations are weighted by the number of observations in the phase of generation life cycle. An elasticity of 0 is used when the observed elasticity is not significant.

* Regression coefficients used in determining elasticities are not statistically significant at the 10% level. NS = not significant.

Third, Table 12 shows the network size effect is almost equal to the quality effect in Growth phase. This result suggests a higher quality console entering the industry during the Growth phase of the generation life cycle may not be able to exploit its quality advantage when faced with a (lower quality) competitor with a large installed base.[15] Fourth, a higher quality console may be at a distinct disadvantage to a lower quality competitor with a large network advantage in the Maturity phase (the network effect is roughly 1.083 (≈16.021/14.799) times the quality effect). Fifth, our results do not rule out the possibility that the network advantage of a lower quality console could cause a higher quality console to exit from the market before the Decline phase—when the quality effect is greatest. The higher quality console will be able to exploit its quality advantage as long as the Decline phase is reached. Sixth, the quality effect in Introduction has a slight advantage over the network effect in Maturity (1.13 ≈ 18.169/16.021) but clearly dominates the network effect in Decline (3.53 ≈ 18.169/5.154). We believe this may provide evidence that larger networks may delay the introduction of new product generations. Potential generational pioneers may delay entry until the effect of their quality advantage is largest.

These results, especially the elasticities, show that the quality and the network effects can vary quite drastically over the generation life cycle. Most importantly, there are situations – Growth and Maturity phases of the generation life cycle, when network effects can trump quality effects. We have solid support for Hypothesis 2.[16]

[15] In fact, the quality advantage in the Growth phase disappears completely when elasticities are calculated at average variable values plus a 1.75 standard deviation increase in console quality and number of available games. At these values, the total elasticity of market share with respect to quality is 18.883 and installed base is 19.110. Here the network effect is roughly 1.01% (≈19.110/18.883) greater than the quality effect.

## Discussion, limitations and further research

This paper examines the relative impacts of quality and network effects over a product generation life cycle in the context of the retail video game industry. As a single product category, video games, consoles and the associated peripherals commanded $25 billion in retail sales in US in 2011 and continue to play a significant role for US retailers. In fact, 76% of sales of this product category in the US occur at traditional retail outlets such as Wal-Mart, Target, and Best Buy (Entertainment Software Association 2011). Therefore, myriad retail managerial decisions such as product assortment and pricing are affected by the relative importance of quality and network effects over the product generation life cycles. Accordingly, the aim of our paper is to provide insights to retail managers, manufacturers and academics regarding the importance of these effects over a generational life cycle.

We extend recent research in marketing in the domain of network and quality effects by Tellis, Yin, and Niraj (2009a) by

[16] Though we do not present the results in this paper, we perform the same elasticity analysis holding the quality effect constant over the generation life cycle while the network effect is allowed to vary. In this case, we find the quality effect empirically dominates the network effect in all phases. In short, Hypothesis 2 is not supported unless we include quality and generation life cycle interaction effects in our analysis. Recall, however, the restriction tests presented in footnotes 12 and 14 suggest adding the quality and generation life cycle interaction effects significantly increases the explanatory power of the regressions. This emphasizes the importance of incorporating life cycle effects: (1) it increases explanatory power and (2) failure to incorporate generation life cycle may result in coefficient biases that disguise the possibility of the network effect trumping the quality effect.

explicitly incorporating the various phases of the product generation life cycle to explore the relative impacts of network and quality effects over the course of a product generation. Our key results can be summarized as follows: (i) We are able to replicate the basic findings of Tellis, Yin, and Niraj (2009a): Both network and quality effects are factors that determine market share (Hypothesis 1); (ii) Network and quality effects in a market vary over the generation life cycle, and hence quality does not always win. In the Growth and Maturity phases of the generation life cycle, network effects can trump quality effects (Hypothesis 2); (iii) The results are robust to alternate specifications of Introduction, Growth, Maturity, and Decline phases of a generation life cycle.

In the economics literature, the overall strong impact of network effects often implies a lock-in and a dominance of an existing product even when the product might have an inferior quality (see, among others, Clements 2005; David 2007; Farrell and Saloner 1986). However, Tellis, Yin, and Niraj (2009a, p. 147) argue that a network need not be a reliable shield to protect incumbents. Constant quality enhancement is an effective way for existing leaders to defend their current positions. Our results confirm the Tellis, Yin, and Niraj (2009a) result *on average*. One retail manager we interviewed confirmed the criticality of console quality in her stocking decision. However, our results also show that during specific phases of the generation life cycle, i.e., Growth and Maturity phases, the network effect can be a reliable shield to thwart entry. In such situations, quality enhancements may not be as effective as in other phases.

A manager (Game Stop) echoed this sentiment regarding quality and network in the Growth and Maturity phases of the life cycle: "As technology ages, specs [quality] become less important. A wide variety of games [network] makes the console seem like a better value." Thus, our analysis suggests that broadening the product assortment of games available to consumers may benefit retailers.

Our results further show that it may be possible for network effects to slow the introduction of a new product generation. Specifically, the network effect is relatively strong during the Maturity phase of the generation life cycle and weaker during the Decline phase. A potential pioneer of a new product generation may have to strategically delay entry until the incumbent has entered the Decline phase. One retail manager underscored this precise fact: ". . .[in the Decline phase] most developers go to the next generation platform," and no new games are slated. Product assortment may be critical for retailers here.

Tellis, Yin, and Niraj (2009a) argue that contrary to the lock-in predictions of economics literature, under certain circumstances, network effects can make the market more efficient. "*A strong network enhances the impact of quality*" (p. 147–148). Our results show that there are some boundary conditions to these findings. Specifically, we see that the network effect is the smallest in the Introduction phase of a generation life cycle, and hence a superior quality can enter and position itself well in the marketplace. Therefore, we find that the network effects may minimally enhance the quality effect, if at all.

On the other hand, recent studies have found that higher quality can attract larger networks thereby reinforcing the effect of superior quality. For example, Gretz (2010b) found that higher quality consoles attracted greater provision of games. A Best Buy manager we surveyed noted that more powerful machines mean a wider range of development - more studios will develop more game titles. Our result in Table 10 echoes this observation; higher quality consoles attract a greater number of games in the Decline phase. Software developers may be more inclined to make games available for higher quality consoles in the Decline phase while they may pass on relatively lower quality consoles. Sony's Jack Tretton advertised this point to software developers when explaining the benefits of developing for PlayStation 3 over its competitors: "'Here we are 4 years into the PlayStation 3, and it's just hitting its stride. We'll enjoy a long downhill roll behind it because the technology that was so cutting edge in 2006 is extremely relevant today and is conspicuously absent in our competition"' (Bosier 2011).

Like prior research, our study has some limitations which could be addressed by future research. First, similar to Tellis, Yin, and Niraj (2009a), we are currently unable to account for advertising or marketing spending as this data is not readily available. Tellis and Fornell (1988, p. 68) find that the effect of advertising on quality is positive and mildly significant. However, quality affects advertising strongly positively in the later phases of the product life cycle. Thus, we might expect both a direct and an indirect (via quality) impact of advertising on market share. Second, similar to Tellis, Yin, and Niraj (2009a), we are unable to account for distributors, especially retailers. However, as long as the retailers do not have brands of their own, they would not be able to exploit network effects differently from the manufacturer brands. Third, we are unable to account for bundling of new products that may enable one firm to promote adoption by including it with its console. For example, Microsoft bundled its Xbox 360 with the very popular game, or "killer application," Halo 3 in September of 2007. It is possible some "killer applications" may significantly affect market share throughout the generation life cycle (see Gretz and Highfill 2010) in a way different than what we present here. Future research should address this aspect. Fourth, while our results are robust to other quality metrics used to analyze the video game industry (Gretz 2010b), another strategy would be to incorporate subjective console quality measures from reviews in trade publications. An interesting methodological challenge would be normalizing reviews over time for inter-generation comparison. One approach may be to use reviews to rank consoles in each generation (with the constraint that consoles from the newest generation are always ranked higher than consoles from a previous generation) and then employ non-parametric analysis. Also, as discussed above in the *Measure of quality* sub-section, there are weaknesses to using the hedonic approach to obtain a summary quality variable in a setting like the video game industry where pricing strategies are dynamic and consumers are heterogeneous. The quality variable we obtain from the hedonic regressions may be more reflective of these considerations than consumers' underlying values of technical characteristics. For example, Liu (2010) shows that console producers have an incentive to charge higher prices early on to obtain rents from high value consumers (i.e. the heterogeneity effect), as well as an incentive to lower prices early on to obtain greater market penetration and exploit a larger network (i.e. the dynamic effect). We argue that these effects may offset each other. Indeed, Liu (2010) finds that including neither effect is a close approximation to including both (and better than including either separately). We save these extensions for future research.

## Appendix A.

Following Clements and Ohashi (2005) and Gretz (2010b), the market for video game consoles is defined as U.S. households with a television set; data is given by The Nielsen Company (http://en-us.nielsen.com/). To calculate the potential market in each month we first find each console's installed base — the total number system purchases before a particular month. The potential market in each month is then the sum of each console's installed base subtracted from the number of U.S. households with a television set. Given this, we define a console's market share of new consumers as the number of new adopters relative to the potential market; the number of consumers who choose the outside option is the sum of all consoles' new adopters subtracted from the potential market.

It should be noted we accommodate the problem of multiple purchases by the same household (or upgrading to a newer console) by letting each console's installed base depreciate at an annual rate of 90% per year.[17] Essentially, the assumption is a single household will not purchase multiple consoles in the same month, but some fraction will purchase an additional console in a later month.

## Appendix B.

This paper employs instrumental variables to correct for possible endogeneity in two of the main explanatory variables in Eq. (1): average console price and the number of available games (including backward compatible games).[18] Average console price is likely correlated with the regression error term, $\xi_t^k$, because unobserved (to the econometrician) console characteristics may be taken into account when the console firm sets profit maximizing price (Zhu and Zhang 2010). Also, the number of games may be influenced by the market share of new consumers; Clements and Ohashi (2005) suggest this is very likely if error terms are autocorrelated.

Three categories of instruments are usually recommended with these types of models: (1) cost shifters uncorrelated with demand, (2) exogenous product characteristics, the sum of exogenous product characteristics of other products offered by the firm, and the sums of competing firms exogenous product characteristics, and (3) the values of endogenous product characteristics in other (independent) markets (Nevo 2000). With regard to the latter, Clements and Ohashi (2005) use average console price in Japan and the exchange rate as an instrument for console price in the U.S. Unfortunately, we were not able to collect data on Japanese console price data for our (larger) selection of consoles and (longer) time frame. Also, we hesitate to use exogenous product characteristics (and the manipulation of those characteristics mentioned above) because of lack of variation in product offerings over the majority of the generation lifecycle. There will be variation at the beginning of a product generation as new consoles enter the market and at the end of a product generation as old consoles leave the market, however, there will be little to no variation during the majority of the generation lifecycle because console offerings are relatively stable. As such, we focus on cost shifters uncorrelated with demand because it is a widely accepted approach (Nevo 2000), we have readily available data, and the cost shifters we employ have been used successfully in previous studies of the video game industry (see Gretz 2010b; Dubé, Hitsch, and Chintagunta 2010).

The challenge is finding instruments that are correlated with the endogenous regressors and uncorrelated with the residuals. As such, following Gretz (2010b) and Dubé, Hitsch, and Chintagunta (2010) we use the producer price indexes for Electronic Computer Manufacturing (ECM), Computer Storage Device Manufacturing (CSDM), and Audio and Video Equipment Manufacturing (AVEM) to control for endogeneity in average console price.[19] Unfortunately, the price indexes do not vary over consoles; they only identify changes in hardware demand (not specific console demand). As a remedy, we employ the product of average game age and console age as an instrument and interact it with ECM, CSDM, and AVEM. The key assumption is manufacturing costs will decline over the generation life cycle; we find this likely given evidence presented in Coughlan (2001). The interaction term is employed because console age is included separately in the estimation equation.

We use producer price indexes for Magnetic and Optical Recording Media Manufacturing (MORMM) and Game Software Publishing (GSP) as a cost side instrument for the number of available games (and backward compatible games).[20] The assumption here is that game development becomes more costly as consoles become more costly because of increased technical ability. We find this likely given the average game development cost for 8-bit, 16-bit, 32/64-bit, and 128-bit hardware is $80,000, $500,000, $1.5 million, and $6 million, respectively (Coughlan 2001).

For the number of available games estimation we are concerned about the endogeneity of the installed base since unobserved shocks in the software market in the previous period can produce an increase in the current period's installed base (Clements and Ohashi 2005). We control for this potential endogeneity by using cost side instruments similar to those used in the hardware demand estimation.

[17] The econometric results are robust to various depreciation rates.

[18] It is unlikely console quality is endogenous since it is determined before a console enters the market.

[19] Data on producer price indexes are obtained from the Bureau of Labor Statistics (http://www.bls.gov/ppi/).

[20] It should be noted the producer price index for Game Software Publishing begins in December, 1997. Year dummies account for dates when the index was not available; we let the value of the variable be zero in periods it was not observed.

First, we employ MORMM and GSP as proxies for industry wide cost shocks. Also, we employ the Consumer Price Index (CPI) as a proxy for economy wide shocks. Similar to the hardware demand estimations, we interact the product of average game age and console age with MORMM, GSP, and CPI to obtain console specific values separate from industry wide and economy wide shocks.

## Appendix C.

In both the console utility estimations and number of available games estimations we test for endogeneity using the well known Hausman test (1978) before using the instrumental variables approach. We find that the Hausman (1978) statistic is significant, and hence, potential endogeneity is present (this verifies the suspicions raised by Reibstein (2009) and Rossi (2009)) and an instrumental variable technique is preferred to OLS. In the next step, we explore the instrument relevance and exogeneity conditions (Stock and Watson 2007; Wooldridge 2003). Instrument relevance tests whether the instruments are correlated with the endogenous variable. A robust and conservative test that is usually reported for instrument relevance is the first stage *F*-statistics developed by Stock and Yogo (2004). The key test for instrument exogeneity is the Hansen *J*-statistic. We find that the instruments are strong: relevant according to the 1-stg *F*-Stats, and exogenous according to the Hansen *J* Statistics. Comparing the coefficients from the OLS estimates to 2SLS and joint GMM estimates imply OLS is biased. As such, we prefer either the joint GMM or 2SLS estimates. Stock, Wright, and Yogo (2002) recommend that the 2SLS estimations should be performed with the generalized method of moments procedure (GMM) in the presence of heteroskedasticity to allow for efficient estimations when the model is over-identified. We use the Pagan and Hall (1983) test to confirm the presence of heteroskedasticity in the hardware estimation: the test statistics (with degrees of freedom in parenthesis) are 148.727 (33) and 68.868 (48) in estimations (3) and (4). The associated p-values are <0.000 and 0.026, respectively. Therefore, we prefer the joint GMM estimation.

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