We especially thank The NPD Group for providing the data used in the research. We also thank the seminar participants at Cornell University, UCLA, and University of Hong Kong Science and Technology as well as the anonymous reviewers for their comments and suggestions. The usual disclaimer applies.
Building on the Resource-Based View of the firm, we advance the idea that a firm’s customer network can be a strategic asset. We suggest that network effects are a function of network size (i.e., installed customer base) and network strength (i.e., the marginal impact of a unit increase in network size on demand). We empirically study these network effects in the 16-bit home video game industry in which the dominant competitors were Nintendo and Sega. In the spirit of the new empirical IO framework, we estimate a structural econometric model assuming the data are equilibrium outcomes of the best fitting non-cooperative game in price and advertising. After controlling for other effects, we find strong evidence that network effects are asymmetric between the competitors in the home video game industry. Specifically, we find that the firm with a smaller customer network (Nintendo) has higher network strength than the firm with the larger customer base (Sega). Thus, our results provide a possible explanation for this situation in which the firm with a smaller customer network (Nintendo) was able to overtake the sales of a firm with a larger network size (Sega). These empirical results suggest that the ultimate outcome in a competitive market with network effects is more complex than simply accepting that the firm with the largest installed customer base will always be the winner.

[Keywords: network externalities; technology lock-in; new empirical industrial organization]
1. INTRODUCTION

In many industries, the network of consumers using compatible products or services influences the benefits of consumption. Positive network effects arise when the consumer utility of using a product or service increases with the number of users of that product or service. The telephone system is a widely used example since it seems clear that the value of being part of the network rises as the network sizes increases. Consumption benefits can also arise in markets where a large customer network leads to increases in complementary products and services, which in turn, leads to increased consumer utility (e.g., see Farrell and Saloner 1985; Katz and Shapiro 1985; 1986). Prominent examples of industries thought to exhibit network effects include automated bank teller machines, computer hardware and software, videocassette recorders, video games, and Internet web browsers. Not surprisingly, network externalities and the implications of having a large installed customer base are receiving increased attention by strategy researchers (e.g., Garud and Kumaraswamy 1993; Hill 1995; Wade 1995).

As noted by Majumdar and Venkataraman (1998), the literature related to network effects broadly tackles three categories of research questions: (1) technology adoption decisions (e.g., what factors are related to whether and when a new technology is adopted), (2) technology compatibility decisions (e.g., what factors influence a firm’s decision to seek compatibility), and (3) decisions among competing incompatible technologies (e.g., what factors are related to consumers’ choices among rival incompatible products within a single product category). While theoretical research has addressed all three of these categories, empirical research has been limited to the first and second categories of questions (e.g., see the reviews in David and Greenstein 1990; Liebowitz and Margolis 1994; Economides 2001).
Empirical efforts supporting the existence of network effects for a single product technology show that a larger network size is related to higher minicomputer sales (Hartman and Teece 1990), higher likelihood of adopting a new telecommunications technology (Majumdar and Venkataraman 1998), and quicker adoption of a new banking technology (Saloner and Sheppard 1995). In addition, Gandal (1994; 1995) and Brynjolfsson and Kemerer (1996) use a hedonic price model to show that consumers are willing to pay higher prices for software products that are compatible with the dominant product standard, i.e., the product with the larger customer network. However, with the exception of a few industry case studies (e.g., Gabel 1991; Grindley 1995; Liebowitz and Margolis 1999), we are unaware of any published studies that empirically investigate the nature of network effects in an industry with multiple competing product technologies that are incompatible.

Consequently, the purpose of this paper is to explore the third category of research questions that has received scant empirical attention, i.e., we investigate the possible network effects that might exist for a set of competing firms with incompatible product technologies. This general situation is important since many markets have more than one product standard in equilibrium. For example, currently in the PC market there are three major operating systems (Windows, Mac and Linux) and in the cellular phone market there are three standards (CDMA, TDMA and GSM). Even the telephone system initially had multiple, competing networks that were incompatible (e.g., Mueller 1997). Voortman (1993) provides an extensive list of industries with competing incompatible technologies. Important questions in this context include the following. Do network effects exist within each competing product technology? What is the nature of these network effects? Are these network effects symmetric across firms? What are the implications of network effects on the outcome of competition among firms with incompatible technologies?
In this paper, we address these questions in the 16-bit home video game industry in which the dominant players were Nintendo and Sega. Following prior empirical research dealing with network effects, we explore these questions in the context of a single industry. While this approach limits the generalizability of our results, it does allow us to explicitly study the dynamics of the competitive interactions between a set of firms. Since our study deals with the competition between two dominant firms, we first develop a game theoretic model of competition. Using monthly time-series data for Nintendo and Sega, we then estimate the network effects for each firm via a structural econometric model assuming the data are equilibrium outcomes of the best fitting non-cooperative game in price and advertising. The contribution of our study is threefold: (1) we provide a theoretical framework for the possible role of network effects in an industry with competing incompatible product technologies, (2) we provide empirical evidence on the nature of these network effects and their implications for competition in a particular industry, and (3) we offer an approach to both analytically and empirically study network effects in a competitive context.

The remainder of this paper is organized as follows. In the next section, we discuss how the Resource-Based View of the firm can be used as a theoretical framework for studying network effects and competition. To furnish a specific context for our model development, we provide some background on the home video game industry and the nature of competition in Section 3. Then, we develop a game theoretic model of duopoly competition in advertising and pricing for the video game industry situation in Section 4. Given the nature of this industry, our model incorporates the possible effects of a firm’s customer network. In Section 5, we discuss the data available for estimation purposes, the estimation results and our interpretation. In Section 6, we
discuss the implications of our findings, and in the last section we discuss the limitations of our study and outline some future research directions.

2. A THEORETICAL FRAMEWORK FOR NETWORK EFFECTS AND COMPETITION

The Resource-Based View suggests that firm capabilities and resources are related to long-term competitive advantage (e.g., Wernerfelt 1984; Barney 1991). Firms can achieve competitive advantage through heterogeneous, rare, and difficult to imitate assets or resources such as organizational culture (Barney 1986), interpersonal relations (Hambrick 1987), firm reputation (Porter 1998), and customer loyalty (Klein and Leffler 1981; Wernerfelt 1984). The Resource-Based View goes on to suggest that how the firm uses its assets is a key determinant of a sustainable competitive advantage.

In this paper, we propose that a firm’s customer network is an important strategic asset that can be used to gain a competitive advantage. A customer network helps a firm gain an advantage by creating an isolating mechanism. An isolating mechanism is a phenomenon that protects a firm from imitation and preserves its rent streams (Rumelt 1984). A firm's customer network can create switching costs for prospective buyers of a competing firm’s products, and thereby create an isolating mechanism (e.g., Montgomery and Wernerfelt 1988; Rumelt 1987). A firm's customer network may also help cement the relationship between the firm and the market, and thus enable it to have a greater claim on the market's rents than its competitors. Such isolating mechanisms form an ex-post limit to competition, enabling a firm to benefit differently than its competitors (e.g., Peteraf 1993). Particularly for incompatible product technologies, installed customer bases are heterogeneous across competitors, and are rare and difficult to imitate.

The effects associated with a customer network are not only a function of network size, but also network strength. A firm’s network size is equivalent to its installed user base, whereas
network strength can be viewed as the marginal impact of a unit increase in network size on demand. Drawing on the community focus theory of Feld (1981) and the social ties of belonging and sharing embedded within groups as described by Homans (1974), the source of a firm’s network strength stems from the customers in its installed base. Importantly, network strength may be based on virtual or physical customer “communities” and can vary across firms (e.g., Balasubramanian and Mahajan 2000). Particularly strong customer networks share a common, underlying (actual or perceived) bond along some important dimension (e.g., personal interests, demographic characteristics, fanatical product loyalty). While some firms are pleasantly surprised with the existence of high network strength for their products (e.g., Apple, Harley-Davidson), others attempt to actively create, manage and leverage their network strength (e.g., Saturn, Amazon.com). For a more complete discussion, see Kawasaki (1992; 1999) and Rosen (2000). A firm’s network strength is a strategic asset because the social ties among members in such a customer network constitute an imperfectly imitable socially complex resource (Barney 1991). In addition, loyalty among members of a firm’s customer base can make network strength a strategic asset (Klein and Leffler 1981; Wernerfelt 1984).

As noted earlier, an installed customer base can positively affect demand when the utility of using a product increases with the number of users of that product, or when a large customer network leads to increases in complementary products and services. In addition, an existing customer network might influence the effectiveness of a firm’s marketing mix decisions such as price and advertising. For example, customers are willing to pay a price premium for Microsoft’s Excel, a spreadsheet product that boasts a large network of users (Brynjolfsson and Kemerer 1996). Similarly, through its “Friends and Family Long-Distance Calling Plan” (that increased the benefits to users when more users joined), MCI dramatically increased the effectiveness of its
limited advertising budget (*Wall Street Journal* 1995). In each of these cases, customer response to a given marketing mix decision (e.g., price and advertising elasticities) is a function of the firm’s customer network.

Thus, network effects can be direct, that is, the direct effect of an installed customer base on demand, or interactive, that is, the effects operate through the interaction of an installed customer base with one or more marketing mix variables such as price and advertising. These interactive network effects are important to consider since they impact the firm’s marketing mix decisions. The total network strength of a firm is reflected in its direct and interactive network effects.

Within this theoretical framework, it is very likely that competing firms will have asymmetric network sizes and, more importantly, network strengths. Although firms with large customer networks may have high network strength (e.g., Microsoft’s Excel), it is also possible to have an industry situation in which a firm with a smaller customer network has high network strength compared to its competitors. We believe that this possibility might help explain common industry examples in which a firm with a smaller customer network was able to effectively compete against a competitor with a larger customer base (e.g., despite its initially smaller customer base, Nintendo’s Super NES video game system eventually overtook the sales of Sega’s Genesis system).

3. THE HOME VIDEO GAME INDUSTRY

In this section, we provide a general overview of the empirical setting. This background information on the video game industry will furnish a specific context to guide the model development in Section 4.

The roller coaster history of the video game industry is well documented in several places (e.g., Cohen 1984; Sheff 1993; Dhebar 1994; Brandenburger 1995a; 1995b). Although this
industry was pioneered by firms like Magnavox (*Odyssey*) and Atari (*Pong*), it wasn’t until Nintendo introduced its 8-bit NES system in 1985 that home video game sales rebounded from its collapse in the early 1980’s. Building on the popularity of games like *Super Mario Brothers* and *The Legend of Zelda*, Nintendo’s 8-bit system was able to capture almost 90% of the market share in the US home video game system industry by 1990 (Brandenburger 1995a). Given its installed base of 30 million units in the US by 1990, Nintendo was really the only significant firm in the 8-bit home video game industry (e.g., Brandenburger 1995a). More advanced 16-bit home video game systems that are the focus of our empirical analysis were introduced in 1989. Given its huge installed base of 8-bit systems, Nintendo waited until late 1991 to introduce a 16-bit system. Sega was thus able to build up a significant installed base for its incompatible 16-bit Genesis system (see Figure 1). To keep the hardware costs down, Nintendo made its new 16-bit NES system backward incompatible with its 8-bit NES system. Nintendo and Sega subsequently engaged in a fierce battle for market leadership in 16-bit systems. Despite Sega’s lead in the 16-bit market, Nintendo was eventually able to take over the leading position in monthly sales of 16-bit systems by mid-1995 (see Table 1).

![Insert Figure 1 and Table 1 about here]

The network effects associated with a large customer base of hardware users are very important in this industry since they are typically associated with increased complementary products (e.g., software titles, licensed products, television cartoon shows, videos and movies)\(^1\), which in turn leads to greater utility and thus greater hardware demand. There are also benefits to

\(^1\)For example, in an interview about why he finally started developing game software for Nintendo, Trip Hawkins (the former CEO of Electronic Arts) said, “Most of the people in the industry thought Nintendo couldn’t succeed. Everyone figured it would be a Cabbage Patch doll kind of thing---that it would hold up for another year and then go the way of Atari and Coleco and the other video game systems that had disappeared…But after a while there were so many Nintendos out that it was a moot point” (*Upside* 1990).
a large user base from the word-of-mouth discussions of game strategies and experiences that take place between users of the same hardware system, as well as from the borrowing and swapping of games (e.g., Monopolies and Mergers Commission 1995).

As noted in the corporate history section of their firm websites, Nintendo (www.nintendo.com) and Sega (www.sega.com) target different demographic groups. In fact, Nintendo’s explicit strategy is to get the younger consumers “hooked on” their video game system in the hopes that these consumers will continue to buy future upgrades of their hardware and software. Compared to Sega, a significantly larger proportion of Nintendo’s customers are young teenagers\textsuperscript{2}. These demographic differences have some important implications for the possible effects of each firm’s customer network. For instance, studies of children’s time use indicate that video games decrease in importance as children age (e.g., Buchman and Funk 1994; Wright et al. 2001). Thus, we expect that Nintendo with its younger customer base will generally have stronger total network effects than Sega. Consumer behavior research also suggests that young teenagers actively search for cues about the “right” products from their peers and from advertising due to their self-uncertainty, desire to belong, and need for approval from others (e.g., Solomon 2002). Thus, it is not surprising that children and teenagers tend to be more sensitive to advertising and less price conscious than adults (e.g., McNeal 1992; Solomon 2002)\textsuperscript{3}. In light of their different demographic user bases, we expect different consumer responses to the advertising and pricing decisions of Nintendo and Sega, i.e., given its younger user base, we expect that Nintendo will have stronger network effects through advertising and price than Sega.

\textsuperscript{2}For example, consistent with each firms’ annual reports, a report by the Monopolies and Mergers Commission (1995) indicates that 64% (54%) of Nintendo’s (Sega’s) main users were less than 17 years old in 1993.

\textsuperscript{3}For example, Pollay et al. (1996) find that the advertising sensitivity for youths is three times that of adults for cigarette advertising.
As already noted, Nintendo and Sega did not compete by changing their 16-bit video game hardware (see also Coughlan 2000). Thus, hardware product quality is invariant within a technology generation. This implies that video game hardware prices do not have to be adjusted for unobserved changes in hardware product quality for our empirical study. Since the technical specifications for each 16-bit hardware system are very similar, consumers’ perceptions of video game software quality plays a critical role in the sales of any hardware system. Nintendo and Sega license other companies to develop the majority of games for their systems (e.g., Dhebar 1994; Brandenburger 1995a; 1995b; Brandt 1995). For example, approximately 90 software producers were developing games for Nintendo in 1990 (Dhebar 1994). Since software has high fixed R&D costs (development costs can be over $500,000 per game title), this outsourcing strategy allows Nintendo and Sega to spread the risks associated with software development (e.g., Dhebar 1994; Brandenburger 1995a; 1995b). To ensure software quality, each firm has very strict licensing contracts with third-party developers (e.g., Dhebar 1994; Brandenburger 1995a; 1995b; Brandt 1995). This resulted in several “cool, killer” games such as Nintendo’s Donkey Kong Country developed by Rare and Sega’s Mortal Kombat developed by Probe Entertainment (Dawley and Eng 1995). The prices of each software cartridge, however, are not set by Nintendo or Sega. Although Nintendo and Sega earn profits by collecting royalties on game software sold by third-party software vendors, the absolute margins on each hardware unit are much higher than the royalties on each software cartridge unit sold. As shown in Table 1 for example, the sales revenues associated with “Top 10” software is dwarfed by that of hardware revenues (i.e., average price multiplied by hardware unit sales). We simplify our analysis by assuming that each hardware firm only makes decisions about its own hardware price and advertising (i.e., firms do not make decisions about software prices).
Although it is usually expected that the behavior of firms is dynamic and based on long term strategic considerations, the very short life cycles of technologies and products in the video game industry suggest that Nintendo and Sega might actually have relatively short profit horizons so as to recover the expenses associated with hardware development and marketing. We confirmed this in two ways. First, industry analysts and government antitrust documents indicate that firms in the video game industry do indeed have short planning horizons and do not usually consider any inter-temporal effects of price and advertising in their decisions (e.g., Monopolies and Mergers Commission 1995). Second, auto-regressive time series analyses of Nintendo and Sega 16-bit price and advertising expenditures showed no significant lag effects (details are available from the authors). These statistical results suggest that the hardware firms’ pricing and advertising decisions are not strategically coordinated over the long term. Thus, in line with other research (e.g., Kadiyali 1996), a repeated game model formulation is used for the video game situation we study.

In summary, the home video game industry is an excellent setting in which to study network effects. The two primary competitors in 16-bit hardware systems, Sega and Nintendo, offered incompatible product technologies. These product technologies were not backward (or forward) compatible with other systems offered in either firm’s product line. Firms in this market did not compete by changing their 16-bit product, but instead competition primarily involved varying hardware price and advertising. The business strategies of Nintendo and Sega centered on their hardware systems, and these firms did not exhibit long term strategic pricing or advertising behavior. By 1993, Nintendo had shifted its emphasis from the 8-bit NES to the 16-bit SNES, and had survived a government antitrust investigation due to its large installed base of 8-bit systems (e.g., Sheff 1993; Dhebar 1994; Brandenburger 1995a; 1995b). These two firms had
asymmetric installed customer bases (at the end of 1992, Sega had an installed base of 6.9 million units and Nintendo only had an installed base of 4.2 million units of 16-bit systems; see Figure 1). Each firm made different hardware pricing and advertising decisions during this period, and obtained different outcomes, i.e., the firm with the smaller installed customer base of 16-bit systems (Nintendo) was able to eventually overtake the firm with the larger installed base (Sega) in monthly demand.

4. A MODEL OF NETWORK EFFECTS AND COMPETITION

A traditional approach to study firm behavior is based on the structure-conduct-performance (SCP) paradigm (e.g., Buzzell and Gale 1987; Porter 1998). According to this paradigm, industry structure (usually measured by factors related to both demand and cost-side effects including concentration, growth, barriers to entry, scale economies, product differentiation) drives industry conduct (defined by factors related to competitive behavior such as marketing mix and strategic decisions), which in turn drives industry performance (e.g., demand, profitability). Assuming that the observed firm decisions are exogenous, studies in this stream typically pool cross-sectional data across several industries to estimate the SCP relationships. Given their breadth of analysis across industries, SCP studies provide generalizable insights into the structural characteristics that make markets profitable and the conduct that is related to profitability (e.g., Kadiyali, Sudhir, and Rao 2001).

However, advances in game theory indicate that market outcomes (e.g., demand) and profitability are not only a function of the broad structural variables used in SCP studies, but also significantly related to market- and firm-specific characteristics (e.g., the different demand and cost structures of competitors, the order of decisions by rivals) as well as rival firms’ strategic decisions (e.g., Moorthy 1993). Thus, to more fully understand the impact of a firm’s strategic
decisions on its performance, we have to simultaneously understand its effects on demand, costs, and competitor reactions. To do this, researchers within the “new empirical industrial organization” (NEIO) tradition develop and estimate structural econometric models where firm decisions are based on profit maximization and the decisions of competing firms are interdependent (i.e., the strategic decisions of one firm cause a reaction from its competitor). This approach has several important features (e.g., Bresnahan 1989; Kadiyali, Sudhir, and Rao 2001): (1) firms make their strategic decisions simultaneously (i.e., firm decisions are endogenous), (2) firm decisions affect demand and demand characteristics affect firm decisions (i.e., realized demand and firm decisions are simultaneously determined), (3) the idiosyncrasies of the major competitors in a single industry are incorporated in the modeling and interpretation of results, (4) the competitive market structure is estimated from the data rather than imposed ex ante on the model formulation, and (5) demand and supply equations are estimated in their structural form rather than their reduced form, with marginal costs recovered as parameters from the estimation.

There are several advantages to the NEIO approach (e.g., Kadiyali, Sudhir, and Rao 2001). Since structural models are based on a behavioral theory of firms (e.g., profit maximization), the estimated parameters have economic meanings that can be directly interpreted. The estimated parameters of structural models are invariant to policy changes (due to the simultaneous consideration of demand, costs, and competitive reactions), allowing for “what if” analyses associated with changes in a firm’s decision variables. The structural approach also provides an opportunity to empirically test alternative theories of strategic interaction since the best fitting model can be considered to represent the particular market situation being studied. These advantages, however, come at a cost. Since NEIO studies consider greater details associated with the competition between firms in a particular situation, they are really only case studies that do not
offer clear generalizations. Instead, generalizations come from the replication of NEIO results across similar competitive situations (e.g., Kadiyali, Sudhir, and Rao 2001).

Given our interest in studying the possible network effects for competing firms with incompatible product technologies, it is important to consider the different demand structures of the competitors (e.g., competitors can have different network sizes and network strengths) as well as the strategic interaction of the competing firms. Thus, we follow the NEIO research approach. Using data from the home video game industry, we will estimate a structural econometric model assuming the data are equilibrium outcomes of the best fitting non-cooperative game in price and advertising. We consider a situation with two firms, each offering its own proprietary and incompatible product technology. Each firm decides on the price and advertising expenditures for its product. We model the direct effects of each firm’s customer network on its demand, as well as possible interactive network effects that may operate through price and advertising. Given the nature of the video game industry, we also consider the possible effects of Nintendo’s (incompatible) installed base of 8-bit systems and the possible effects due to firm differences in software quality.

4.1 The Demand Model

We consider a situation of two competing firms, each having a demand function of the following form:

\[
Q_{it} = e^{\alpha_i} P_{it}^{-\eta_i} A_{it}^{\beta_i} P_{jt}^{\delta_j} A_{jt}^{\gamma_j} \quad i \neq j
\]

Here, \(Q_{it}\) = firm i’s demand at time t, \(P_{it}\) = firm i’s price at time t, and \(A_{it}\) = firm i’s advertising expenditures at time t. Further, \(\alpha\) is the parameter for brand-specific effects, \(\eta\) and \(\beta\) are the own price and advertising elasticities, and \(\delta\) and \(\gamma\) are the cross-price and cross–advertising elasticities. All the parameters are assumed to be non-negative. Consistent with prior research that finds
asymmetric price and advertising elasticities across firms (e.g., Carpenter, et al. 1988), we do not impose any constraints that these parameters must be equal across competitors. In line with the published empirical literature, we also expect that there is diminishing marginal returns to advertising \((\beta_i < 1, \gamma_i < 1)\) and the own price elasticity \(\eta_i\) is greater than one. This particular demand function is used for several reasons. First, the multiplicative form in price and advertising generally describes market behavior well. Second, interactions are embedded in this formulation since the marginal effect of one variable is a function of the level of the others. Third, this model form is analytically tractable, allowing closed-form equilibrium solutions to be obtained\(^4\).

In line with other empirical studies of network effects (e.g., Hartman and Teece 1990; Brynjolfsson and Kemerer 1996; Majumdar and Venkataraman 1998), we consider firm \(i\)’s 16-bit network size at time \(t\), \(B_{16_t}\), to be exogenously determined. This simplifying assumption seems reasonable for exploring the role of network effects in a competitive situation characterized by firms with short planning horizons (i.e., this analysis should at least provide a lower bound on possible network effects). Further, we also consider the effects of firm \(i\)’s software quality at time \(t\), \(K_{it}\), since it is expected to influence firm \(i\)’s demand, as well as the effectiveness of its price and advertising\(^5\). Finally, we control for the possible effects of Nintendo’s existing installed base of 8-bit systems at time \(t\), \(B_{8_{Nt}}\).

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\(^4\)A linear demand function could also be considered. However, a linear model has no optimal properties in advertising (i.e., there is no first-order solution). In contrast, the multiplicative model does not have this problem and, additionally, has the desirable property that its parameters directly provide the elasticities.

\(^5\)Software quality is treated as exogenous in our analysis (i.e., we assume that software quality is independent of its hardware firm’s demand, price and advertising). We take this approach for three reasons. First, a Hausman (1978) test indicates that software quality is not endogenous for the video game data we study in the next section. Second, even though Nintendo and Sega had different installed customer bases, demand, advertising and prices, both had licenses with all of the major third party software developers so that the same titles can appear in both formats. Third, a “killer” game is a rare occurrence. As noted by Nintendo executives, “Our video games are an art form and their developers are a group of artists” (Dhebar 1994). Although a mega-hit title could return 200-300 times their costs in less than a year, only about 10% of released games earn a profit and nearly half of all
We note that empirical studies of network effects using product category level data are often beset by the following problem: since average category prices and costs are usually decreasing over time due to technological advances, it is generally difficult to identify whether increasing category demand is due to network effects or simply to lower prices. However, in our analysis using firm-level data this problem is not as severe since: (1) video game hardware quality does not change within a technological generation, (2) monthly hardware prices for each firm do not necessarily decline over time, and (3) we control for software quality differences between firms and the possible effects of an installed base of prior product technology.

Letting $\alpha_{1i}$ be firm i’s direct network effect coefficient, we incorporate the direct effects of a firm’s customer network through the exponential intercept term in the demand equation (1):

$$
\alpha_{Ni} = \alpha_{0Ni} + \alpha_{1Ni} B16_{Ni} + \alpha_{2Ni} K_{Ni} + \alpha_{3Ni} B8_{Ni}
$$

$$
\alpha_{Si} = \alpha_{0Si} + \alpha_{1Si} B16_{Si} + \alpha_{2Si} K_{Si}
$$

Here, $\alpha_{0i}$ captures possible brand-specific effects that are constant over time and not explicitly accounted for by the other variables. We also include appropriate terms in (2) for $K_{Ni}$ and $B8_{Ni}$. Following the established literature on network effects, we expect that $\alpha_{0i}$, $\alpha_{1i}$, $\alpha_{2i}$ and $\alpha_{3Ni}$ are non-negative. Our primary interest is in the parameters $\alpha_{1Ni}$ and $\alpha_{1Si}$, both of which we expect to be positive.

The possible influence of a customer network on the effectiveness of a firm’s price decision is captured through its own elasticity:

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game titles sell less than 10,000 copies (Coughlan 2000). Thus, it is very difficult to predict the future success of any video game title as a function of hardware decisions.
\[ \eta_{Ni} = \eta_{0N} - \eta_{1N} B16_{Ni} - \eta_{2N} K_{Ni} - \eta_{3N} B8_{Ni} \]
\[ \eta_{Si} = \eta_{0S} - \eta_{1S} B16_{Si} - \eta_{2S} K_{Si} \]

Similarly, the possible influence of a customer network on the effectiveness of a firm’s advertising decision is modeled as:

\[ \beta_{Ni} = \beta_{0N} + \beta_{1N} B16_{Ni} + \beta_{2N} K_{Ni} + \beta_{3N} B8_{Ni} \]
\[ \beta_{Si} = \beta_{0S} + \beta_{1S} B16_{Si} + \beta_{2S} K_{Si} \]

Here, \( \eta_{0i} \) and \( \beta_{0i} \) are the own price and own advertising elasticities, respectively. Our primary interest however, is in \( \eta_{1i} \) (firm i’s price-network size coefficient) and \( \beta_{1i} \) (firm i’s advertising-network size coefficient). These coefficients represent the interactive network effect of firm i’s customer base on its price and advertising effectiveness. Following the theoretical and empirical literature dealing with network effects, price sensitivity is expected to decrease as the network size increases (i.e., \( \eta_{1i} \geq 0 \) or customers will be willing to pay more for a product technology supported by a large network of users due to an expected increase in complementary products; Gandal 1994; 1995; Brynjolfson and Kemerer 1996). Similarly, advertising is likely to be more effective as the network size increases (i.e., \( \beta_{1i} \geq 0 \) or firms with a large network can maintain their demand with less advertising expenditures due to scale efficiencies associated with a larger “buzz factor” around the expected increase in complementary products; Mas-Colell, Whinston, and Green 1995). As software quality increases, we also expect that price and advertising sensitivities will decrease and increase, respectively. Finally, a large installed base of prior product technology (\( B8_{Ni} \)) is expected to be associated with lower price and higher advertising sensitivities for Nintendo. It follows that \( \eta_{0i} > 1 \) (since \( \eta_{it} > 1 \) and \( \eta_{1i}, \eta_{2i}, \eta_{3N}, B_{it} \geq 0 \)) and \( \beta_{0i} < 1 \) (since \( \beta_{it} < 1 \) and \( \beta_{1i}, \beta_{2i}, \beta_{3N}, B_{it} \geq 0 \)).
4.2 The Competitive Situation

We view the duopolistic competition between firms as one of repeated games of strategic interaction\textsuperscript{6}. Repeated games enable firms to enhance their positions vis-à-vis a one shot game and can reflect the long-term nature of strategic competition between firms (e.g., Gasmi and Vuong 1991; Gasmi, Laffont and Vuong 1992; Kadiyali 1996). The unique equilibria in repeated games of finite duration are the same as those in a stage game played in every period (Fudenberg and Tirole 1992)\textsuperscript{7}.

The profit for firm i at time $t$ is:

\[ \Pi_i(t) = (P_i(t) - c_i)Q_i(t) - A_i - F_i \]  \hspace{1cm} (5)

where $c_i$ is the marginal cost and $F_i$ is the fixed cost of production for firm $i$. Since technological products have relatively short life cycles, we assume marginal costs are constant for each firm; this is also consistent with the NEIO approach (Bresnahan 1989)\textsuperscript{8}.

Firms simultaneously maximize their profits by choosing their own price and advertising expenditure levels. Other noncooperative games that we considered in the course of our research included several Stackelberg leader-follower structures (e.g., see Gasmi and Vuong 1991; Gasmi, Laffont and Vuong 1992; Kadiyali 1996; Shankar 1997). We do not discuss any of these

\textsuperscript{6}Note however, that the actual behavior in the market studied need not be described by a proposed game structure. To determine whether any particular game structure adequately represents the available market data, convergence of estimates and model fit are examined. Thus, the formulations we consider should be viewed as an “as if” story (e.g., see Gasmi and Vuong 1991; Gasmi, Laffont and Vuong 1992).

\textsuperscript{7}We study a finite horizon because the length of a technology’s life cycle is generally finite (e.g., 8-bit is superceded by 16-bit, which is eventually superceded by 32-bit, etc.). This approach is consistent with other studies (e.g., Gasmi and Vuong 1991; Kadiyali 1996; Shankar 1997).

\textsuperscript{8}We tested the validity of this assumption for the home video game data by dropping six observations from the beginning of the data series and then re-estimating our models. We repeated this analysis by dropping six observations from the end of the data series. The results from these analyses did not reveal any significant difference in the marginal costs, suggesting that the marginal costs of the firms remained constant over the period of our data.
alternative competitive situations here since the video game data we analyze in the next section: (1) do not exhibit any strong leader-follower patterns, and (2) did not generate convergent estimates for any other possible leader-follower game structure in price and advertising.

Based on the demand model (1) and the profit function (5), the Nash equilibria in price and advertising can be derived from the first order conditions. Details of the equations to be estimated, along with a discussion of the estimation approach are in the Appendix. We expect that at least one of the parameters related to the network strength of Nintendo to be greater than the corresponding parameter of Sega. These parameters include those for the direct network effect and the interactive network effects through price and advertising. That is, we expect at least one of the following: $\alpha_{1N} > \alpha_{1S}; \eta_{1N} > \eta_{1S}; \beta_{1N} > \beta_{1S}$.

5. AN EMPIRICAL ANALYSIS

In this section, we provide an empirical analysis of the competitive game with network effects formulated in the previous section. We first describe the data available for estimation purposes and the measures for the key variables. We then discuss the empirical analysis and results.

5.1 Data

The data available for estimation purposes include monthly time-series information between January 1993 and August 1995 for Nintendo and Sega 16-bit hardware sales (units), hardware price (dollars), advertising expenditures (millions of dollars), and installed customer base size (units) for the 16-bit systems (and Nintendo’s 8-bit system)$^9$. In addition, data on

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$^9$Even though there are only 32 observations, the general approach discussed in Section 4 and the Appendix makes it nearly impossible to over-fit the data since the parameter estimates must satisfy all the conditions imposed by our six simultaneous equations (see also Kadiyali 1996). In practice, it is generally difficult to even achieve estimation convergence for models in this research stream (see the discussion in Gamsi and Vuong 1991; Gamsi, Laffont, and Vuong 1992; Kadiyali 1996). We also note that the results reported in the next section are
sales of the top 10 software titles (i.e., “killer” games) for each system (millions of dollars) is used as our measure of software quality\textsuperscript{10}. A summary of this information is in Tables 1 and 2. Sales and price information come from The NPD Group, a leading organization that tracks this industry. The sales data are based on a sample of 17 leading US retail chains that account for 65% of the video game systems sold. The average monthly price is computed by dividing the monthly dollar value of sales by the volume of units sold. Advertising information for the 16-bit systems comes from the \textit{Broadcast Advertising/Leading National Advertisers (BAR/LNA)} reports published by Competitive Media Reporting. To obtain monthly advertising figures, we divided the original quarterly values using a uniform distribution of spending. We confirmed the reasonableness of this assumption with the industry experts who provided the video game data. Since the Sega Genesis and Nintendo SNES systems were introduced before the start of our data series, the January 1993 value of each firm’s installed customer base was obtained from Brandenburger (1995b). Given the wide range in values for the original data, natural logarithms of the network size variables (B16, and B8, ) and software sales were used in the empirical analysis to stabilize the variation within these variables\textsuperscript{11}. Also, dummy variables are included in the demand functions (via Equation 2) for November and December due to

\textsuperscript{10}The term “Top 10” software is used by the videogame industry to denote the best selling or most popular titles. This value includes sales revenues for the best selling games developed by Nintendo/Sega or third party developers. Unfortunately, an explicit, objective measure of videogame software quality is unavailable. We note that firms in this industry believe that the top 10 titles are more representative of software “quality” than the breadth of all titles (typically, the number of titles is comparable across video systems and software prices within each system are very similar across titles). What really matters though, is consumer acceptance of these titles (i.e., software sales). Thus, we use sales of “Top 10” software as a proxy for software quality.

\textsuperscript{11}We also note that the inter-correlations for these log-transformed variables are lower than those of the original variables for the video game data we study.
seasonal considerations. Finally, analysis of the correlations among the independent variables showed that multicollinearity was not a problem for these data.

5.2 Estimation Results

We estimated the model using both 3SLS and GMM methods. The advantage of the 3SLS method is that each individual equation can be estimated. GMM, on the other hand, is more appropriate for obtaining efficient estimates if the errors are heteroscedastic. The 3SLS and GMM estimation results for our model of network effects and competition appear in Tables 3 and 4, respectively. Because a Glesjer (1969) test showed that heteroscedasticity is not a problem for our data, it is not surprising that the results are very similar.

From Tables 3 and 4, the signs of the coefficients are intuitive and reasonable. The network effects associated with each firm’s 16-bit installed base are generally significant. Software “quality” has significant main effects, as well as significant effects through price, for both Nintendo and Sega. With the exception of price, the effects of Nintendo’s prior product technology are insignificant. Own price and advertising elasticities are significant for both firms, as are the cross-price elasticities. The significant results for the November and December dummy variables are consistent with the seasonal nature of demand in this industry.

Importantly, the parameters associated with the 16-bit network effects ($\alpha_{1i}$, $\eta_{1i}$, $\beta_{1i}$) are significant for at least one of the firms. These results indicate that the home video game industry does indeed exhibit network effects as proposed in the theoretical economics literature. As indicated by the third column in Tables 3 and 4, the coefficients relating to the direct effect of network size ($\alpha_{i1}$) of Nintendo and Sega are not statistically different at the 0.05 level, consistent
with the assumption in most theoretical studies\(^\text{12}\). However, the difference between the firms’ price-network size coefficients (\(\eta_{1i}\)) is significant at the 0.05 level, as is the difference between the firms’ advertising-network size coefficients (\(\beta_{1i}\))\(^\text{13}\). These results reflect asymmetry for the competitors in network strength through advertising and price; specifically, they are more favorable for Nintendo.

From Table 1, it is clear that between 1993 and 1995 Sega maintained a substantially larger installed base of 16-bit systems than Nintendo. In addition, both firms made different advertising and pricing decisions. This is particularly evident in 1995 in which Nintendo spent almost twice as much in advertising than Sega, and had a higher price. Despite Sega’s initial lead in earned gross profits\(^\text{14}\), Nintendo was able to just surpass Sega’s level of profits during the months leading to August 1995 (see Table 5). The estimated gross profits paths for Sega and Nintendo during 1995 appear in Figure 2. At the same time, Nintendo was able to pass Sega in unit sales during 1995 (see Table 1). The sales trajectories for Nintendo and Sega during 1995 are shown in Figure 3. The parameter estimates in Table 3 provide a possible explanation for this observed behavior. The demand parameters of Nintendo are either comparable with, or more favorable than, Sega’s parameters. In particular, Nintendo has stronger interactive network effects through price and advertising than Sega. These strong network effects may have contributed to a decision to have

\(^{12}\)The tests of coefficient differences in this case and in the subsequent cases incorporate the cross-covariances between the relevant parameters.

\(^{13}\)Another possible explanation for these data is that the interactive network effect coefficients are symmetric across firms, but they are concave functions of network size. To test for this possibility, a model with \(\eta_{1i}=\eta_{1j}\), \(\beta_{1i}=\beta_{1j}\) (i.e., equal coefficients for Nintendo and Sega), and quadratic in B16it was also subsequently estimated. Convergent estimates could not be obtained, suggesting that this alternative model formulation is not consistent with our data.

\(^{14}\)Using the estimates in Table 3, along with the demand equation (1) and profit equation (5), monthly profits for each firm can be calculated. Since we have no information on the fixed costs of production, we can only construct estimates of each firm’s gross profits.
higher equilibrium advertising expenditures and prices, which in turn, enabled Nintendo to eventually catch and surpass Sega in monthly demand.

[insert Table 5, Figure 2 and Figure 3 about here]

An interesting result is that the cross-price elasticities are significant, but the cross-advertising elasticities are insignificant. Given that the home video game industry is characterized by incompatible hardware systems and unique game software (e.g., Nintendo’s Super Mario Brothers and Donkey Kong versus Sega’s Sonic the Hedgehog and Mortal Kombat), the advertising of each system appeals to its own consumer segment and firms primarily compete for new customers to the market (e.g., Carlton 1995; Dawley and Eng 1995). Due to the inherent nature of incompatible systems, the home video game industry seems to represent a setting in which demand is elastic with respect to its own price and advertising as well as competitive pricing, but is unresponsive to advertising of the closest substitute product.

In summary, after controlling for various possible asymmetries between competitors, we find that each firm’s 16-bit customer network has a direct effect on its own hardware demand and interactive effects through its own hardware price and advertising. More important, we find strong evidence of asymmetric interactive network effects between the competitors.

5.3 “What if” Analyses

The implications of higher network strength helping the firm with the smaller installed base (Nintendo) are shown in Table 6. Table 6 provides three “what if” scenarios (i.e., three combinations of price and advertising levels) that shows the number of months needed for Nintendo (with superior network strength) to catch up with the established leader, Sega, for a given difference in installed customer base and Nintendo’s price and advertising levels. Since our focus is on the role of network effects, all other variables are set to the average values in the
database and are assumed to be the same for the two firms. For comparability, the effect of Nintendo’s 8-bit installed base is also excluded from the computation.

The base scenario represents Nintendo’s average price and advertising levels during 1993-95. In this case, it would take about 22 months for Nintendo to catch up with Sega if the installed base deficit is 2.7 million (which was the case at the start of 1993), but only 8 months if the deficit is 1 million. The first scenario allows us to look at the advertising-network size interactive effect. Average monthly advertising for Nintendo is higher than Sega’s expenditures by $0.2 million (about 5%). Because of a favorable advertising-network size interactive effect, Nintendo would be able to catch up with Sega in just five months if its installed base, at the starting point, is lower than Sega’s by 1 million. The second scenario enables us to examine the price-network size interactive effect. In this case, the advertising level is the same as in Scenario 1, but Nintendo’s price is reduced by $4 (about 5%). The time to catch up to Sega varies from 21 months (for an installed base of 2.7 million) to 7 months (for an installed base of 1 million). Thus, a 5% change in advertising has a greater impact than a 5% change in price on Nintendo’s ability to quickly catch up to Sega in monthly sales.

6. DISCUSSION

In several industries for which network effects are important, a common situation is one in which there are multiple competing product technologies that are incompatible (e.g., Voortman 1993). Today, for example, there are several competing wireless communication standards, as well as several digital audio, video and graphic formats. When competing firms have incompatible and proprietary products, theory suggests that a competitive advantage accrues to the firm with largest customer network or installed base (e.g., Katz and Shapiro 1985; 1986; 1992;
Farrell and Saloner 1985; 1986; Besen and Farrell 1994). Of particular interest is the theoretical result that in markets with strong and symmetric network effects across competitors, situations of technology “lock-in” can be obtained. In other words, once a particular product technology gains any small lead over competing technologies in terms of its customer network size, there is a tendency for the technology with the larger network to become the industry standard (e.g., Arthur 1994; 1996). This result implies that under some conditions, an inferior product with a lead in establishing its own network will ultimately win out over a superior product (e.g., David 1985).

As noted by Hill (1995), network externalities and the possibility of lock-in also suggests that firms with competing technology standards should attempt to build their installed customer bases as quickly as possible.

Despite the logic of these theoretical arguments, there is scant empirical support for the underlying model assumptions (e.g., see the reviews in David and Greenstein 1990; Liebowitz and Margolis 1994; Economides 2001). With the exception of a few industry case studies (e.g., Gabel 1991; Grindley 1995; Liebowitz and Margolis 1999), we are unaware of any empirical studies that investigate the nature of network effects for the situation of multiple competing product technologies that are incompatible. This is important since the implications of the theoretical research depend on the empirical nature of the underlying network effects relative to other competitive effects. In particular, these theoretical models do not allow asymmetric network effects for the competitors (i.e., the effects of a specific network size are assumed to be equivalent for each firm). If asymmetric network effects do exist, then it may still be possible for a later entrant with a smaller starting network size to successfully compete. Asymmetric network effects might also help explain common industry examples in which a firm with a large customer network was eventually overtaken by a competitor that began with a smaller customer base. Thus, it really
seems presumptuous at this point to use the general recommendations from this theoretical research stream in developing business and competitive strategies.

Consequently, this paper seeks to add to our empirical understanding of network effects. We study the possible asymmetric network effects between firms in a competitive situation using the NEIO framework. Using data on the two dominant hardware competitors in the 16-bit home video game industry, Nintendo and Sega, we estimated a structural econometric model assuming the data are Nash equilibrium outcomes in a noncooperative game in price and advertising.

Recall that we started out by asking three related research questions: Do network effects exist within each competing product technology? What is the nature of these network effects? Are these network effects symmetric across firms? Consistent with most theoretical models’ assumption that the direct effect of a customer network on demand is symmetric across competitors (e.g., Katz and Shapiro 1985; 1985; 1992; Farrell and Saloner 1985; 1986), we find that the network size coefficients of Nintendo and Sega are significant but not statistically different (see $\alpha_{1i}$ estimates in Tables 3 and 4). In agreement with the hedonic price models for computer spreadsheet software (e.g., Gandal 1994; 1995; Brynjolfson and Kemerer 1996), we find that price effectiveness of Nintendo and Sega is a function of network size (see $\eta_{1i}$ estimates in Tables 3 and 4). In addition, we find that each firm’s advertising effectiveness is influenced by its relative network size (see $\beta_{1N}$ estimate in Tables 3 and 4). Our empirical results also show that Nintendo and Sega have asymmetric network effects since the interactive network strength values through price and advertising are statistically different for the two firms (see $\eta_{1i}$ and $\beta_{1}$ estimates in Tables 3 and 4). These asymmetric network strength values may help explain why Nintendo was able to pass Sega in monthly sales of 16-bit home video game systems despite Sega’s larger installed base.
Although it is only anecdotal in nature, it is interesting to note that Nintendo seemed to continue its successful 16-bit systems competitive strategy in the advanced video game systems market. In a bid to regain its lead in the home video game industry, Sega leaped ahead of Nintendo by introducing its 32-bit Saturn system in May 1995. Sony soon followed with its new 32-bit PlayStation system in September of that year. Once again, Nintendo delayed its entry of a competing advanced game system. As in the 16-bit market, this allowed Sega and Sony to establish large installed customer bases. By the time Nintendo introduced its N64 system in September 1996, Sega had already sold one million Saturn systems and Sony had sold 2.1 million PlayStation systems. As with its 16-bit SNES system, Nintendo seemed to use advertising and promotion for its advanced game system more extensively than its competitors. Despite a later start, once again monthly sales of Nintendo’s N64 quickly caught Sega and Sony. According to John Taylor of Arcadia Investment Management Corp., “Nintendo took its sweet time bringing the N64 to market, but they did a lot of things right” (Browder, Brull and Reinhardt 1997). As in the case of 16-bit systems, Nintendo’s N64’s advertising, driven by its stronger network effects over its rivals, seems to have been an important factor in the success of the N64 video game system. However, despite their hold on the loyalty of game players under 14 years old, the continued demographic expansion of video game households into older age groups suggests that Nintendo’s network strength advantage over its rivals may be fading (e.g., Alexander and Associates 2001). In addition, more recent events (e.g., the huge lead of Sony’s PlayStation2 and the recent entry of Microsoft’s Xbox) raise the question of whether Nintendo (with its new GameCube) will be able to continue relying on their old strategy (e.g., Gaither 2001).

Our last research question concerned the implications of network effects on the outcome of competition among firms with incompatible technologies. Assuming that network effects are
symmetric, the firm with the largest installed base of customers is generally thought to have an advantage over its competitors. However, our results indicate that network effects can depend on the size of the installed customer base and the network strength associated with its direct effect and with its interactive effects through price and advertising. Moreover, the strength of each firm’s installed customer base can be different, leading to asymmetric network effects. As a result, a firm that has a relatively small installed base may compete successfully if it has adequately high network strength that can favorably impact the sales response to its price and advertising. Moreover, these results highlight the fact that the ultimate outcome in a competitive market with network effects is more complex than simply accepting that the firm with the largest installed customer base will always be the winner.

Given the importance of differences in network strengths among competitors, a firm may want to actively manage and leverage its customer network. For example, Nintendo understood the demographic composition of its younger user base and put together a marketing program to exploit its network strength. This included heavy spending on advertising, as well as its own magazine (Nintendo Power), cartoon show, and movie (e.g., Monopolies and Mergers Commission 1995). Similarly, MCI used its friends and family plan to take full advantage of its limited advertising budget (Wall Street Journal 1995).

7. LIMITATIONS AND FUTURE RESEARCH

As is the case with all research, due caution should be exercised in generalizing our findings beyond the specific industry, time period, and data sample used in this study. In fact, an inherent limitation to our NEIO approach is the lack of clear strategic generalizations. Instead, we provide estimates of, and insights about, the underlying competitive structure, demand and network effects for the two dominant firms in the 16-bit home video game industry. Our findings in this
specific context suggest potential directions for future replications. For example, do firms with high network strength through advertising follow the more aggressive advertising and pricing strategy used by Nintendo? Do firms with a large customer network price higher than a competitor with a smaller network? Do firms with strong network effects enter later than their competitors and still emerge as an important market player?

Since the video game industry is characterized by heterogeneous consumer tastes (i.e., there is no “winner-take-all” video game system), a stronger empirical test of a late entrant’s ability to catch up to a competitor may come from studies in other industry settings (e.g., video cassette recorders, personal computer operating systems, spreadsheet software packages). For example, are network effects equal across competitors in other industries? Do competing firms in other markets exhibit asymmetric network effects? In what other ways, possibly involving other marketing mix variables such as distribution, do firms exhibit asymmetric network effects? Although a static model formulation is adequate for the video game data we study, dynamic models may be required for other industry settings. Further research along these lines will extend our understanding of network effects and competition.

To our knowledge, no analytical (or empirical) models have considered the potential implications of asymmetric network effects in a competitive situation. Thus, normative decisions dealing with technology adoption, entry timing, and pricing in markets with asymmetric network effects are unknown. For example, do competing firms desire product compatibility when one firm has stronger network effects than the other? Are there any first-mover advantages when a later entrant has stronger network effects? Addressing these questions would seem to be a promising direction for future analytical research. Empirical investigation of the sources of asymmetric network effects would also yield further insights. This effort, however, would
require cross-sectional data on multiple markets with network effects. Although this would pose a considerable data challenge, it is a fruitful avenue for future research.
Appendix

To obtain the Nash equilibria for the competitive game, we examine the first-order conditions. Taking the derivative of (5) with respect to $P_{it}$ and simplifying, we obtain:

$$P^*_{it} = \frac{\eta_{it} c_i}{(\eta_{it} - 1)} \quad (A1)$$

Taking the derivative of (5) with respect to $A_{it}$ and simplifying, we obtain:

$$A^*_{it} = (P^*_{it} - c_i) \beta_{it} Q_{it} = \frac{\beta_{it} c_i Q_{it}}{(\eta_{it} - 1)} \quad (A2)$$

We note that Equations (A1) and (A2) are consistent with the results of Dorfman and Steiner (1954).

Substituting (3) and (4) into Equation (A1), we obtain the structural equations for equilibrium price:

$$P^*_{nt} = \frac{(\eta_{0N} - \eta_{1N} B16_{nt} - \eta_{2N} K_{nt} - \eta_{3N} B8_{nt}) c_N}{(\eta_{0N} - \eta_{1N} B16_{nt} - \eta_{2N} K_{nt} - \eta_{3N} B8_{nt} - 1)}$$

$$P^*_{st} = \frac{(\eta_{0S} - \eta_{1S} B16_{st} - \eta_{2S} K_{st}) c_S}{(\eta_{0S} - \eta_{1S} B16_{st} - \eta_{2S} K_{st} - 1)} \quad (A3)$$

Substituting (3) and (4) into Equation (A2), we obtain the structural equations for equilibrium advertising:

$$A^*_{nt} = \frac{(\beta_{0N} + \beta_{1N} B16_{nt} + \beta_{2N} K_{nt} + \beta_{3N} B8_{nt}) c_N Q_{nt}}{(\eta_{0N} - \eta_{1N} B16_{nt} - \eta_{2N} K_{nt} - \eta_{3N} B8_{nt} - 1)}$$

$$A^*_{st} = \frac{(\beta_{0S} + \beta_{1S} B16_{st} + \beta_{2S} K_{st}) c_S Q_{st}}{(\eta_{0S} - \eta_{1S} B16_{st} - \eta_{2S} K_{st} - 1)} \quad (A4)$$

From Equation (A3), we can see that a larger network size ($B_{it}$) is associated with a higher equilibrium price. In addition, strong interactive network effects through price ($\eta_{1i}$) are associated
with a higher equilibrium price. We note that equilibrium price is independent of the interactive effects through advertising in Equation (A3). Similarly, from Equation (A4) we can see that larger network size \((B_{it})\) results in higher equilibrium advertising expenditures for a given level of demand. Equilibrium advertising spending increases with advertising-network size \((\beta_{1i})\), but may decrease with price-network size \((\eta_{1i})\) for a given level of demand. In this case, equilibrium advertising is dependent on the interactive network effects through price. Because equilibrium demand and profits depend on equilibrium price and advertising, they are thus determined by the net impact of any network effects. Larger network size by itself does not automatically lead to higher demand or profits. The strength of these network effects (including the direct effects associated with a customer network as well as the interactive effects of this customer network on the effectiveness of price and advertising) also plays an important role in the determination of equilibrium demand and profits.

The demand model (1) and equilibrium equations (A3) and (A4) for each firm lead to a system of six simultaneous nonlinear equations. In estimating this system of three equations for each firm, we assume a multiplicative error term for each equation. These error terms are not required to be normally distributed. We identify the parameters by imposing constraints on the parameters as provided by the equilibrium conditions and the assumed coefficient restrictions. Since Equations (1), (A3) and (A4) do not involve the fixed costs, we are not interested in estimating \(F_i\).

The system of six equations to be estimated for the two firms come from equations (1), (A3) and (A4). We note that there is a maximum of sixteen parameters in any one equation. The six endogenous variables are \(Q_{it}, P_{it}, A_{it} (i=1,2)\) and the twenty-two predetermined variables are \(\text{NOV}_t, \text{DEC}_t, \text{B16}_t\) and \(K_{it}\) for each firm, \(\text{B8}_ {N_t}\) for Nintendo, six 16-bit interaction
variables (i.e., demand, price, and advertising interactions for each firm), six software quality interaction variables, and three 8-bit network size interaction variables. Each equation is identified in the above system according to the order condition involving included endogenous and excluded predetermined variables (see Kelejian and Oates 1989 for a discussion of identification issues for nonlinear simultaneous equation systems). The demand equation of each firm has five included endogenous variables (one demand variable, two price, and two advertising variables), and at least ten excluded predetermined variables (one 16-bit network size variable, one software quality variable, two 16-bit network size-demand interaction variables, two software quality-demand interaction variables, a 16-bit network size-price interaction variable, a 16-bit network size-advertising interaction variable, a software quality-price interaction variable, and a software quality-advertising interaction variable). Each price equation has one included endogenous variable (price variable) and at least sixteen excluded predetermined variables (one 16-bit network size variable, one software quality variable, two seasonal dummies, five 16-bit network size interaction variables, five software quality interaction variables, and two 8-bit network interaction variables). Finally, each advertising spending equation has two included endogenous variables (one advertising variable and one demand variable) and sixteen excluded predetermined variables (two 16-bit network size variables, two seasonal dummies, two software quality variables, one 8-bit network size variable, four 16-bit network size interaction variables, four software quality interaction variables, and one 8-bit network size interaction variable). Thus, in each equation, the number of excluded predetermined variables is at least as great as the number of included endogenous variables less one, and the order condition is satisfied.
Similarly, it can be shown that the rank condition is satisfied and therefore the system is identified. The number of restrictions for structural coefficients in each equation is adequately high. For example, for Equation (1) the number of exclusion restrictions is 14 and 16 for Nintendo and Sega, respectively. For equation (A3), the number of exclusion restrictions is 16 and 18 for Nintendo and Sega, respectively. For equation (A4), the number of exclusion restrictions is 15 and 17 for Nintendo and Sega, respectively. In addition, there are additional restrictions on the structural parameters in Equations (A3) and (A4), totaling to 25. The rank of the product of the X matrix and the restriction matrix in each equation is equal to the number of endogenous variables in the system less one (i.e., five), thus satisfying the rank condition for identification (Kalejian and Oates 1989).

The rank condition can also be determined using the following alternative approach. For each of the six equations, the rank of the relevant sub matrix in the structural form-reduced form transformation matrix is at least equal to the number of endogenous variables less one. For each equation in (1), the rank of the relevant sub matrix is four, which is the number of endogenous variables (demand, own price, own advertising, competitor price, and competitor advertising) less one. For equations in (A3), the relevant sub matrix has a rank of zero. This is the same as the number of endogenous variables (price) less one. For equations in (A4), the rank of the relevant sub matrix is one, equal to the number of endogenous variables (advertising and demand) less one. Finally, we can also see that the specification of each of the structural equation in the system is such that no two equations are observationally equivalent. Therefore, the rank condition is satisfied. The computation of the ranks of the sub matrices of the structural form-reduced form transformation matrix is very technical and long and is not shown here. It is available upon request from the authors.
In addition, multicollinearity is not a severe problem for the home video game data as shown in the correlation matrix of key independent variables below. As we noted earlier, the inter-correlations for the log-transformed variables are lower than those of the original variables for the video game data we study. The major effect of any correlation between two independent variables in an equation is on the variances of the parameter estimates. However, hypotheses tests on the parameters are still unaffected (Green 2000). In our situation, these correlations are not believed to be problematic because these estimates turn out to be significant.

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<th>Sega Advertising</th>
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*Because installed base is measured as a percentage for this table, Nintendo’s installed base is 1 less Sega’s installed base.
REFERENCES


Table 1
Annual Summary of Data for the US Home Video Game Industry

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<td>Top 10 Software Sales</td>
<td>19.2</td>
<td>66.0</td>
<td>36.0</td>
</tr>
<tr>
<td><strong>Sega 16-bit</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Top 10 Software Sales</td>
<td>56.4</td>
<td>50.4</td>
<td>34.8</td>
</tr>
<tr>
<td><strong>Nintendo</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Advertising Expenditures</td>
<td>46.4</td>
<td>47.2</td>
<td>22.5</td>
</tr>
<tr>
<td><strong>Sega</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Advertising Expenditures</td>
<td>46.9</td>
<td>40.7</td>
<td>11.6</td>
</tr>
<tr>
<td><strong>Nintendo 16-bit</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Price</td>
<td>120</td>
<td>115</td>
<td>122</td>
</tr>
<tr>
<td><strong>Sega 16-bit</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Price</td>
<td>112</td>
<td>118</td>
<td>114</td>
</tr>
</tbody>
</table>
Table 2
Summary Statistics of Monthly Data for the US Home Video Game Industry

<table>
<thead>
<tr>
<th></th>
<th>Mean (s.d.)</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nintendo 16-bit</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unit Sales (in thousands)</td>
<td>128 (126)</td>
<td>42</td>
<td>620</td>
</tr>
<tr>
<td>Sega 16-bit</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unit Sales (in thousands)</td>
<td>159 (201)</td>
<td>43</td>
<td>1039</td>
</tr>
<tr>
<td>Nintendo 8-bit</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Installed Base (in millions)</td>
<td>25.9 (1.1)</td>
<td>25.7</td>
<td>26.0</td>
</tr>
<tr>
<td>Nintendo 16-bit</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Installed Base (in millions)</td>
<td>6.3 (1.3)</td>
<td>4.2</td>
<td>8.2</td>
</tr>
<tr>
<td>Sega 16-bit</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Installed Base (in millions)</td>
<td>9.6 (1.7)</td>
<td>6.9</td>
<td>11.9</td>
</tr>
<tr>
<td>Nintendo 16-bit</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Top 10 Software Sales (in $ millions)</td>
<td>3.23 (6.26)</td>
<td>0.44</td>
<td>34.70</td>
</tr>
<tr>
<td>Sega 16-bit</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Top 10 Software Sales (in $ millions)</td>
<td>4.06 (4.90)</td>
<td>0.27</td>
<td>19.27</td>
</tr>
<tr>
<td>Nintendo</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Advertising Expenditures (in $ millions)</td>
<td>3.72 (3.60)</td>
<td>0.71</td>
<td>16.90</td>
</tr>
<tr>
<td>Sega</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Advertising Expenditures (in $ millions)</td>
<td>3.10 (2.51)</td>
<td>1.03</td>
<td>9.74</td>
</tr>
<tr>
<td>Nintendo 16-bit</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Price (in $)</td>
<td>118.8 (3.8)</td>
<td>111.1</td>
<td>124.2</td>
</tr>
<tr>
<td>Sega 16-bit</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Price (in $)</td>
<td>114.5 (4.6)</td>
<td>106.8</td>
<td>124.0</td>
</tr>
</tbody>
</table>
Table 3
3SLS Estimation Results (n = 64)
(standard errors in parentheses)
System-wide $R^2$=0.63

<table>
<thead>
<tr>
<th>Network Effects</th>
<th>Nintendo Coefficient Estimates</th>
<th>Sega Coefficient Estimates</th>
<th>Test of Coefficient Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Direct Effect ($\alpha_1$)</td>
<td>1.71 (0.76)*</td>
<td>1.93 (0.78)**</td>
<td>not significant</td>
</tr>
<tr>
<td>Price-Network Size Interactive Effect ($-\eta_1$)</td>
<td>0.10 (0.04)*</td>
<td>0.06 (0.02)*</td>
<td>significant**</td>
</tr>
<tr>
<td>Ad-Network Size Interactive Effect ($\beta_1$)</td>
<td>0.08 (0.03)*</td>
<td>0.03 (0.10)</td>
<td>significant**</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Control Variables</th>
<th>Nintendo Coefficient Estimates</th>
<th>Sega Coefficient Estimates</th>
<th>Test of Coefficient Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firm-Specific Effects ($\alpha_0$)</td>
<td>6.34 (2.71)**</td>
<td>6.14 (4.13)</td>
<td>significant*</td>
</tr>
<tr>
<td>Software Quality ($\alpha_2$)</td>
<td>1.65 (0.54)**</td>
<td>1.76 (0.51)**</td>
<td>not significant</td>
</tr>
<tr>
<td>8-bit Network Size ($\alpha_{3N}$)</td>
<td>0.33 (0.61)</td>
<td>NA</td>
<td>not significant</td>
</tr>
<tr>
<td>November Seasonal Effects ($\alpha_4$)</td>
<td>0.70 (0.14)**</td>
<td>0.57 (0.24)**</td>
<td>not significant</td>
</tr>
<tr>
<td>December Seasonal Effects ($\alpha_5$)</td>
<td>1.42 (0.18)**</td>
<td>1.42 (0.18)**</td>
<td>not significant</td>
</tr>
<tr>
<td>Own Price Elasticity ($-\eta_0$)</td>
<td>-3.23 (1.34)*</td>
<td>-3.46 (1.45)*</td>
<td>not significant</td>
</tr>
<tr>
<td>Price-Software Quality ($-\eta_2$)</td>
<td>0.0025 (0.001)*</td>
<td>0.0031 (0.001)*</td>
<td>not significant</td>
</tr>
<tr>
<td>Price-8-bit Network Size ($-\eta_{3N}$)</td>
<td>0.06 (0.03)*</td>
<td>NA</td>
<td>significant*</td>
</tr>
<tr>
<td>Own Advertising Elasticity ($\beta_0$)</td>
<td>0.13 (0.04)*</td>
<td>0.21 (0.09)*</td>
<td>not significant</td>
</tr>
<tr>
<td>Ad-Software Quality ($-\beta_2$)</td>
<td>0.003 (0.011)</td>
<td>0.0013 (0.0094)</td>
<td>not significant</td>
</tr>
<tr>
<td>Ad-8-bit Network Size ($-\beta_{3N}$)</td>
<td>0.08 (0.12)</td>
<td>NA</td>
<td>not significant</td>
</tr>
<tr>
<td>Cross-Price Elasticity ($\epsilon$)</td>
<td>0.28 (0.11)*</td>
<td>0.20 (0.10)*</td>
<td>significant*</td>
</tr>
<tr>
<td>Cross-Advertising Elasticity ($-\gamma$)</td>
<td>-0.03 (0.13)</td>
<td>-0.05 (0.11)</td>
<td>not significant</td>
</tr>
<tr>
<td>Marginal Cost (k in dollars)</td>
<td>54.67 (18.12)**</td>
<td>59.32 (21.27)**</td>
<td>significant*</td>
</tr>
</tbody>
</table>

*significant at 0.05 level
**significant at 0.01 level
Table 4

GMM Estimation Results (n=64)
(standard errors in parentheses)
System-wide $R^2 = 0.67$

<table>
<thead>
<tr>
<th></th>
<th>Nintendo Coefficient Estimates</th>
<th>Sega Coefficient Estimates</th>
<th>Test of Coefficient Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Network Effects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Direct Effect ($\alpha_1$)</td>
<td>1.72 (0.73)*</td>
<td>1.91 (0.79)**</td>
<td>not significant</td>
</tr>
<tr>
<td>Price-Network Size Interactive Effect (-$\eta_1$)</td>
<td>0.11 (0.04)*</td>
<td>0.06 (0.02)*</td>
<td>significant**</td>
</tr>
<tr>
<td>Ad-Network Size Interactive Effect ($\beta_1$)</td>
<td>0.09 (0.03)*</td>
<td>0.03 (0.11)</td>
<td>significant**</td>
</tr>
<tr>
<td><strong>Control Variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm-Specific Effects ($\alpha_0$)</td>
<td>6.28 (2.75)**</td>
<td>6.09 (4.04)</td>
<td>significant*</td>
</tr>
<tr>
<td>Software Quality ($\alpha_2$)</td>
<td>1.62 (0.53)**</td>
<td>1.75 (0.58)**</td>
<td>not significant</td>
</tr>
<tr>
<td>8-bit Network Size ($\alpha_{3N}$)</td>
<td>0.37 (0.73)</td>
<td>NA</td>
<td>not significant</td>
</tr>
<tr>
<td>November Seasonal Effects ($\alpha_4$)</td>
<td>0.72 (0.16)**</td>
<td>0.53 (0.23)**</td>
<td>not significant</td>
</tr>
<tr>
<td>December Seasonal Effects ($\alpha_5$)</td>
<td>1.41 (0.21)**</td>
<td>1.37 (0.34)**</td>
<td>not significant</td>
</tr>
<tr>
<td>Own Price Elasticity (-$\eta_0$)</td>
<td>-3.25 (1.40)*</td>
<td>-3.50 (1.43)*</td>
<td>not significant</td>
</tr>
<tr>
<td>Price-Software Quality (-$\eta_2$)</td>
<td>0.0024 (0.001)*</td>
<td>0.0029 (0.001)*</td>
<td>not significant</td>
</tr>
<tr>
<td>Price-8-bit Network Size (-$\eta_{3N}$)</td>
<td>0.06 (0.03)*</td>
<td>NA</td>
<td>significant*</td>
</tr>
<tr>
<td>Own Advertising Elasticity ($\beta_0$)</td>
<td>0.12 (0.03)*</td>
<td>0.21 (0.08)*</td>
<td>not significant</td>
</tr>
<tr>
<td>Ad-Software Quality (-$\beta_2$)</td>
<td>0.002 (0.017)</td>
<td>0.001 (0.010)</td>
<td>not significant</td>
</tr>
<tr>
<td>Ad-8-bit Network Size (-$\beta_{3N}$)</td>
<td>0.09 (0.14)</td>
<td>NA</td>
<td>not significant</td>
</tr>
<tr>
<td>Cross-Price Elasticity ($\varepsilon$)</td>
<td>0.27 (0.10)*</td>
<td>0.21 (0.10)*</td>
<td>significant*</td>
</tr>
<tr>
<td>Cross-Advertising Elasticity (-$\gamma$)</td>
<td>-0.04 (0.19)</td>
<td>-0.05 (0.14)</td>
<td>not significant</td>
</tr>
<tr>
<td>Marginal Cost (k in dollars)</td>
<td>53.91 (21.44)**</td>
<td>58.84 (22.10)**</td>
<td>significant*</td>
</tr>
</tbody>
</table>

*significant at 0.05 level
**significant at 0.01 level
Table 5
Estimated Gross Profits of Nintendo and Sega for 16-bit US Home Video Game Systems

<table>
<thead>
<tr>
<th></th>
<th>1993</th>
<th>1994</th>
<th>Through August 1995</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Nintendo Gross Profits</strong> (in $ millions)</td>
<td>82.5</td>
<td>57.0</td>
<td>13.2</td>
</tr>
<tr>
<td><strong>Sega Gross Profits</strong> (in $ millions)</td>
<td>87.2</td>
<td>73.9</td>
<td>13.2</td>
</tr>
</tbody>
</table>
Table 6

“What If” Scenario Analysis:
Time Required for Nintendo To Catch Up or Equal Sega in Monthly Sales

<table>
<thead>
<tr>
<th>Installed Base Difference (millions)</th>
<th>Base Scenario</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Price ($), Ad. ($m), No. of months</td>
<td>% Δ Ad., No. of months</td>
<td>% Δ Price, No. of months</td>
</tr>
<tr>
<td>2.7</td>
<td>$118, 3.7, 22</td>
<td>+5%, 20</td>
<td>-5%, 21</td>
</tr>
<tr>
<td>2.0</td>
<td>$118, 3.7, 17</td>
<td>+5%, 15</td>
<td>-5%, 16</td>
</tr>
<tr>
<td>1.5</td>
<td>$118, 3.7, 13</td>
<td>+5%, 10</td>
<td>-5%, 12</td>
</tr>
<tr>
<td>1.0</td>
<td>$118, 3.7, 8</td>
<td>+5%, 5</td>
<td>-5%, 7</td>
</tr>
<tr>
<td>0.5</td>
<td>$118, 3.7, 4</td>
<td>+5%, 2</td>
<td>-5%, 4</td>
</tr>
</tbody>
</table>

Assumptions

Based on parameter estimates from Table 4. All other variables have the average values in the database and are assumed to be the same for the two firms. For comparability across scenarios, the effect of Nintendo’s 8-bit installed base is excluded from computations. The percentage change of 5% over the Base Scenario in price and advertising is based on the average value of Nintendo’s price and advertising in the data (see Table 2).
Figure 1

Growth in Installed Base of 16-bit US Home Video Game Systems
Figure 2

Estimated Monthly Gross Profits of Nintendo and Sega During 1995
Figure 3

Monthly Sales of Nintendo and Sega During 1995

[Graph showing monthly sales of Nintendo and Sega from January to August 1995.]