Network Externalities in Hardware/Software Systems: An Econometric Analysis of the Video Game Industry

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14.33 Final Paper
April 25, 2003

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1 Introduction

A product creates network externalities when the utility derived from consuming that product increases as others consume the same product. Network externalities have been used to explain why consumers are reluctant to switch away from popular products, even though such products might be physically or technologically inferior to other products in the market. Examples of industries that are expected to have network externalities include the computer industry and the telecommunications industry. This paper investigates
network externalities in the video game industry. There are several reasons to believe that network externalities exist in the video game industry. First, since the software that is used on these hardware consoles can be costlessly traded, one would expect a consumer to prefer a console that has a large base of users, so that he could exchange games with friends. Second, software manufacturers prefer to develop games for consoles with a large base of users to maximize their potential profits. Lastly, a large base of users creates a knowledge base about the console.

This paper considers six hardware systems (consoles) sold between 1990 and 2000. Consoles can be thought of as differentiated products that are made up of various hardware characteristics. Since the hardware characteristics of each console are well known\(^1\), they should play a role in the determination of each console’s price. In addition to hardware characteristics, the price of a console might also be related to the number of consoles that have already been sold. If a consumer’s valuation of a particular console increases as more are sold, then direct network externalities exist in the market for video game consoles.

There has been considerable research about network externalities in many industries, using a variety of specifications to explore the presence of network externalities. This paper uses a hedonic model and a demand model to explore the existence of direct network externalities in the video game industry.

2 Previous Work

A product creates network externalities when the utility that an individual derives from consuming the product increases with the number of other individuals consuming the same product. Katz and Shapiro (1985) develop a model to analyze such products using the following utility function:

\[
    u_i = a_i + b_i \cdot N_e \\
    b_i > 0
\]

\(a_i\) can vary among consumers, allowing for heterogenous preferences. \(N_e\) is the expected size of the network of the compatible goods. \(b_i\) captures the positive relationship between network size and utility. According to Katz and Shapiro, network externalities can be classified and explained by:

1. Indirect effect: Consider a hardware/software system. Consumers of hardware want other consumers

\(^1\)The hardware specifications of each console are provided by the manufacturer.
to also purchase similar and compatible hardware because it will affect the amount and variety of available software. Since hardware owners derive additional utility from the availability of quality software, the network of hardware owners produces an indirect network effect.

2. Direct effect: The user base generates the externality. Examples include telephones, cellular networks, and fax machines. The larger the network, the larger the benefits.

3. Knowledge/Service base: Externalities can depend on the size of the service network, which likely varies with the number of products that have been sold in the market. An example is the automobile industry.

The following sections describe the empirical evidence of indirect and direct network externalities in different industries.

2.1 Indirect Network Externalities

Gandal (2000) proposes and empirically evaluates a two-way feedback model for CD players. Cottrell and Koput (1998) investigate hardware and software in the computer industry from 1981 to 1986. They use the following model:

\[ P_h = f(M_h, N_h, V_s) \]  

(2)

where \( P_h \) is the price of the hardware product, \( M_h \) is its market share, \( N_h \) is the sales of the good, and \( V_s \) is a measure of software variety. \( M_h \) captures the direct network externalities, while \( V_s \) captures the indirect network externalities. Cottrell and Koput find all variables to be highly significant, with the expected sign.

2.2 Direct Network Externalities

Gandal (1994) measures direct network externalities in the market for spreadsheet software from 1986 to 1991. His regression model is

\[ P_{it} = f(C_{it}, NC_{it}, T_t) \]  

(3)

where \( P_{it} \) is the list price, \( C_{it} \) is a vector of compatibility attributes, \( NC_{it} \) is a vector of non-compatibility attributes of software package \( i \) at time \( t \). \( T_t \) is a time trend variable. Compatibility attributes include
Lotus compatibility, external database compatibility, and local area network compatibility. Gandal finds all compatibility variables to be highly significant. Since compatible products strengthen network externalities, Gandal concludes that direct network externalities exist in the market for spreadsheet software.

Brynjolfsson and Kemerer (1996) correct Gandal’s self-acknowledged limitation of not including a variable that directly measures the effect of the network externalities. They modify Gandal’s model to include a variable to directly measure network externalities on the RHS. They use the following hedonic price model:

\[ P_{it} = f(N_{it}, S_{it}, F_{it}, T_{i}) \]  

(4)

where \( P_{it} \) is the list price, \( N_{it} \) is a vector of network externality attributes, \( S_{it} \) is a vector of standards attributes, \( F_{it} \) is a vector of product feature attributes, and \( T_{i} \) is the time trend of software package \( i \) at time \( t \). The network externalities variable is the installed base share of the software package. The standards variable is a dummy that indicates whether the product supports the Lotus 1-2-3 menu tree feature. The regression results indicate high statistical significance in both the network externality and standard variables. Other studies on direct network externalities include Saloner and Shepard (1990) on the adoption of ATMs and Greenstein (1992) on the market for IBM mainframes.

3 Data

The data for this paper were assembled from several sources. To use a hedonic model to estimate the effect of network externalities, product attributes are needed to control for differences among the consoles that are not related to network externalities. These attributes were taken from the manufacturer of each console. The sales and market price data were taken from a case study on the video game industry by Thompson and Strickland (1999). The cost data for computer memory were taken from Saltzer and Kaashoek (2002). The data set is complete; there are no omitted values. The data set contains only 49 observations \(^2\), which unfortunately restricts the explanatory power of the models \(^3\).

The data set contains the market prices, sales histories, and product characteristics of six consoles sold between 1990 and 2000. Each entry includes the market price, the year, an integer to identify the console, the sales of the console that year, the cumulative sales up until that year (non-inclusive), and feature attributes

\(^2\)Three of the six consoles were first sold after 1995, and therefore do not have observations before then.

\(^3\)Any analysis of fixed effects has been left out entirely to minimize the number of variables on the RHS.
for that console. The market price ($PRICE$) is actually the MSRP for that year. Because most stores sell
the consoles at or around the MSRP, it should closely approximate the market price. The annual sales ($QD$)
are given in millions of units, and these values represent the quantities of each good demanded during the
year. The installed base for the console ($HWBASE$) is the sum of all previous sales. The features attributes
give a broad description of the console's underlying technology. These attributes are processor speed, size of
computer memory, and bits of color ($CPU$, $RAM$, and $COLOR$). Descriptions of all variables can be found
in Table 1.

For the hedonic regressions used in this paper, other variables were defined and derived from the data set.
Their descriptions are found at the bottom of Table 1. $TREND$ is derived from the $YEAR$ variable and it
is included in the regressions to de-trend the data. Using a trend variable instead of fixed effects for each
year is preferable given the smallness of the data set.

Table 2 presents descriptive summary statistics for all the variables used in the analysis. The data set
is complete; all observations contain entries for each variable. No observations are dropped in the analysis.
Note that $TREND$ measures the years after 1990; therefore it has a range from 0 to 10, corresponding to
the spread in the $YEAR$ variable.

Technologically, the consoles vary across the CPU speed, computer memory, and color quality. There
is also a large range and deviation in the $PRICE$ variable. This demonstrates that the data set contains
diverse products with varying characteristics.

4 Methods

This paper develops two econometric models to analyze network externalities in the video game industry,
and only analyzes direct network externalities. While the data set used for this paper includes statistics
on software sales and market shares, these variables are very highly correlated with the hardware variables.
Therefore, it is difficult to separate the direct from the indirect network externalities. This paper has thus
focused on direct network externalities that result from the physical size of the network (the number of users
of the particular console), as measured by either the size of the installed base or the level of market share.

The first model is a hedonic model that estimates how the console's market share affects consumers’
worthiness-to-pay (as proxied by the market price). The second model is a demand model that estimates
how the installed base affects the quantity of consoles demanded by consumers. In this paper, the installed
base, $B_{it}$, of console $i$ at time $t$ is defined as the cumulative sales of the console up to and including the previous year:

$$B_{it} = \sum_{j=1}^{i-1} Q_{ij}$$  (5)

$B_{it}$ is estimated by the HWBASE variable in the data set, which appears in the demand model. The market share, $M_{it}$, of console $i$ at time $t$ can be defined using the installed base values for all consoles in the sample. The formula is

$$M_{it} = \frac{B_{it}}{\sum_{j \in C} B_{jt}}$$  (6)

where $C$ is the set of all consoles in the universe, and $M_{it}$ is the market share of console $i$ at time $t$. $M_{it}$ is estimated by the HWSHARE variable in the data set, which appears in the hedonic model. Both variables ($B_{it}$ and $M_{it}$) are used to measure the presence of direct network externalities in the market for video game consoles. The decision to use $B_{it}$ in one model and $M_{it}$ in the other model is intentional. There is reason to suspect that both the size and share of the installed base would affect consumers’ valuations of the product. An additional 1 million units added to the installed base should have a positive effect on utility, even if the market share declines because of larger increases among other products. An increase in market share without a corresponding increase in the installed base (by other products leaving the market) could also be expected to increase utility by making the product relatively more attractive. Therefore, both variables are used in this paper to estimate the same direct network externality. $M_{it}$ is used in the hedonic model (see Section 4.1) because that is the model proposed by Brynjolfsson and Kemerer (1996).

### 4.1 Hedonic Model

A hedonic regression requires a data set that contains a set of characteristics and market prices for a particular product. The analysis involves a regression of prices on the variables that represent the relevant characteristics of the product being studied. Adapting the model proposed by Brynjolfsson and Kemerer (1996), the hedonic model takes on the following form:

$$P_{it} = f(M_{it}, F_{it}, T_{it})$$  (7)
where $M_{it}$ is the market share that measures the presence of direct network externalities, $F_{it}$ is a vector of product feature attributes, and $T_i$ is the time trend of console $i$ at time $t$. Note that this model differs from the Brynjolfsson-Kemerer model because there are no standards attributes for video game consoles. A standards attribute variable is omitted because there is no software cross-compatibility among any of the consoles in the sample \(^4\). Using the data set described in the previous section, a base econometric specification based on the model above takes the following form:

$$\log PRICE = \beta_0 + \beta_1 HWSHARE + \beta_2 RAM + \beta_3 COLOR + \epsilon_1$$  \hspace{1cm} (8)

The coefficient $\beta_1$ (the effect of increasing market share on the price of the console) motivates the decision to enter the PRICE in log form. Other things being equal, as the market share of a console increases, it is reasonable to assume that the price of the console increases as a percentage of the current price.

A second hedonic regression can extend the base specification (equation (8)) and attempt to de-trend the data by adding a first-order trend variable. This results in the following specification:

$$\log PRICE = \beta_0 + \beta_1 HWSHARE + \beta_2 RAM + \beta_3 COLOR + \beta_4 TREND + \epsilon_2$$  \hspace{1cm} (9)

Equation (9) is identical to (8) with the additional trend variable added to de-trend the data. Since technological advances cause console prices to generally decrease in price over time, the addition of the TREND variable should control for technological change.

These regressions compose the hedonic analysis of the effect of various characteristics on the price of consoles, and they test for the presence of direct network externalities in the market for video game consoles. If the estimate for coefficient $\beta_1$ were positive and significant in both regressions, then that would be evidence of existence of network externalities. In addition to the hedonic specification, this paper also develops a demand model that tests for the presence of network externalities.

\(^4\)There is likely a standards effect in the video game industry, but it is much more subtle that the user interface standards that Brynjolfsson and Kemerer analyze. By adhering to certain standards in hardware design, hardware manufacturers can allow for more efficient software development. This can create an indirect network externality that motivates the production of quality software. The limitations of the data set prevented analyzing this issue, but it would be an interesting area for future research.
4.2 Demand Model

The hedonic model does not allow for price to vary inversely with the quantity of consoles demanded. This paper includes a second model, based on the interaction of demand and supply equations. The simultaneous equations determine the annual price and quantity for a given console. The simultaneous equations take the following form:

\[
Q^d_{it} = f(B_{it}, F_{it}, P_{at}, T_t) \quad (10)
\]

\[
Q^s_{it} = g(P_{it}, C_{it}) \quad (11)
\]

where \(Q^d_{it}\) and \(Q^s_{it}\) represent the quantity demanded and supplied for console \(i\) at time \(t\). These quantities are identical at equilibrium. \(P_{it}\) is the market price of console \(i\) at time \(t\), and is expected to vary inversely with \(Q^d_{it}\) and positively with \(Q^s_{it}\). As in the hedonic model, \(B_{it}\) is the installed base, and \(F_{it}\) is a vector of feature attributes. \(C_{it}\) is a vector of input costs. Since only the coefficient \(B_{it}\) is important to the analysis of network externalities, it is not necessary to econometrically specify the entire demand-supply model. Rather, the demand model can be specified as follows:

\[
QD = \beta_0 + \beta_1 HWBASE + \beta_2 CPU + \beta_3 RAM + \beta_4 COLOR + \beta_5 PRICE + \beta_6 TREND + \epsilon_1 \quad (12)
\]

This equation (12) is an econometric specification of the general demand equation above (10). Since it is part of a simultaneous equation system (\(P_{it}\) is endogenous), Ordinary Least Squares (OLS) estimation will lead to biased and inconsistent estimates. Therefore, in order to identify the demand equation, we need to instrument for \(PRICE\). The variable \(HW\) \(\text{COST}\) is used to instrument for \(PRICE\) in equation (12). This variable is chosen because it affects \(PRICE\) as an input cost, while it is likely uncorrelated with the error term in the demand equation.

The decision to include \(TREND\) in equation (12) is motivated by the recognition that consoles are less appealing over time because of technological progress. The \(TREND\) variable should pick up the decreasing preferences for a particular console over time as more technologically advanced consoles become available.

The hedonic model and demand model both estimate the significance of the installed base. The variable in the hedonic model is the market share of the installed base, while the variable in the demand model is
the size of the installed base itself. If the coefficients of both variables were estimated to be positive and statistically significant, then it would provide evidence for direct network externalities in the market for video game consoles.

5 Results

Table 3 presents the results from the hedonic regressions. The first column uses equation (8) as the specification. All variables are statistically significant at the 10% level. Recall that the dependent variable is the natural log of the market price of the console. Therefore, the interpretation of the 0.074 coefficient of COLOR is that an additional bit of color increases market price by 7.4%. The HWSHARE coefficient is statistically significant at the 10% level. Its interpretation is somewhat more complicated because HWSHARE is constrained to be in the range of [0,1]. A HWSHARE value of .2 means that the console has a 20% market share. The interpretation of the HWSHARE variable, therefore, is that an increase of 10 percentage points in market share increases the market price by 6.1% (.61 / 10). Note that the $R^2$ for this regression is only .267, meaning that this base regression is not particularly explanatory.

The second column in Table 3 presents results from a richer specification that uses equation (9) to de-trend the data. The addition of the trend variable checks the robustness of the base results, and controls for pricing trends over time. The magnitudes of some of the coefficients are affected by the introduction of the trend variable. For instance, the RAM variable increases from 0.316 to 0.365. This implies that the base regression mistakenly included some of the trend effects in the RAM coefficient. The estimate of the coefficient of HWSHARE decreases substantially from 0.610 to 0.241. The interpretation of the HWSHARE variable is the same; an increase of 10 percentage points in market share increases the market price by 24%. Adding the TREND variable, however, results in estimates that are more statistically significant. The de-trended regression also has a much larger $R^2$. Since both coefficient estimates of HWSHARE are positive and statistically significant, the hedonic regressions imply that there are direct network externalities.

Table 4 presents the results from the regressions using the demand model. Equation (12) is used as the specification. The first column presents the regression results of equation (12) without instrumenting for the endogenous PRICE variable. The second column uses HWCOST to instrument for PRICE. The results in the first column are presented only for comparison; because of the endogeneity, only the results in the second column are unbiased estimates. The results in table 4 show that using the instrumental variable sacrifices some statistical significance for unbiasedness. The coefficient on HWBASE is still statistically
significant at the 5% level. The interpretation of the coefficient is that an additional 1 million units in the installed base will increase the quantity demanded by 332,000 units. Note that the coefficient estimate of \textit{HW\textsc{BASE}} actually increases after the instrumental variable has been introduced. Also, the results of the IV regression show that the coefficients on the \textit{PRICE}, \textit{CPU}, \textit{RAM}, and \textit{COLOR} variables are not statistically significant. The positive and statistically significant coefficient of \textit{HW\textsc{BASE}} is evidence that direct network externalities exist in the market for consoles.

The statistical significance of the estimates of the \textit{HW\textsc{SHARE}} and \textit{HW\textsc{BASE}} coefficients suggests that direct network externalities exist in the market for video game consoles. A larger data set could use less constrained models to precisely determine the magnitude of the network externalities. Efforts have been made in this paper to test the robustness of these results. The hedonic model was de-trended to control for price declines over time; the demand model used an instrumental variable to control for endogeneity.

6 Conclusion

The findings strongly suggest that there are direct network externalities in the market for video game consoles. The magnitude of the effect was estimated separately using a hedonic model and a demand model. In both models, the coefficient on the variable measuring the direct network externality is statistically and economically significant. In the hedonic model, the de-trended regression estimated that an increase in market share by 10 percentage points increases the price by 2.4%. In the demand model, the regression using instrumental variables estimated that a 1 million unit increase in the installed base will increase the quantity of consoles demanded by 332,000. These results suggest that the size and share of the network of consoles affects consumers’ valuations of the product. Future studies can analyze indirect network externalities by using the data for software sales, installed software base, software market share, and software variety. Also, to check the robustness of these results, a larger data set that includes more consoles and spans a larger range of years could be compiled. The larger data set could yield a more precise estimate of the coefficient measuring the direct network externalities. Data for recent consoles (Playstation 2, GameCube, XBox) could support or refute the conclusions of this paper. Lastly, it is clear that pricing in the video game industry is strategic. Therefore, more robust models could more precisely estimate the effect of network size on consumers’ valuations by controlling for firms’ strategic pricing.
7 References


8 Tables

8.1 Table 1: Definition of Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>PRICE</td>
<td>Console price</td>
</tr>
<tr>
<td>QD</td>
<td>Quantity of console demanded</td>
</tr>
<tr>
<td>HWBASE</td>
<td>Console’s installed base</td>
</tr>
<tr>
<td>HWSHARE</td>
<td>Console’s market share</td>
</tr>
<tr>
<td>YEAR</td>
<td>Year for entry</td>
</tr>
<tr>
<td>SYSTEM</td>
<td>System ID</td>
</tr>
<tr>
<td>CPU</td>
<td>Processor speed (in MHz)</td>
</tr>
<tr>
<td>CDROM</td>
<td>1 if console accepts CDs, 0 otherwise</td>
</tr>
<tr>
<td>RAM</td>
<td>Computer Memory (in MB)</td>
</tr>
<tr>
<td>COLOR</td>
<td>Bits of color</td>
</tr>
<tr>
<td>HWCOST</td>
<td>Cost of Disk Memory</td>
</tr>
<tr>
<td>TREND</td>
<td>Years after 1990</td>
</tr>
<tr>
<td>LOGP</td>
<td>Log of PRICE</td>
</tr>
<tr>
<td>LOGHWCOST</td>
<td>Log of HWCOST</td>
</tr>
</tbody>
</table>

System IDs are as follows: 1=Sega Saturn; 2=Nintendo 64; 3=Playstation; 4=SNES; 5=Genesis; 6=NES
### Table 2: Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs.</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>HWSHARE</td>
<td>49</td>
<td>.2244898</td>
<td>.2111796</td>
<td>.0042017</td>
<td>.9645454</td>
</tr>
<tr>
<td>HWBASE</td>
<td>49</td>
<td>12.17551</td>
<td>7.6067</td>
<td>.3</td>
<td>23.1</td>
</tr>
<tr>
<td>PRICE</td>
<td>49</td>
<td>135.1224</td>
<td>63.04153</td>
<td>49</td>
<td>399</td>
</tr>
<tr>
<td>CPU</td>
<td>49</td>
<td>20.03286</td>
<td>27.62767</td>
<td>1.79</td>
<td>93.5</td>
</tr>
<tr>
<td>CDROM</td>
<td>49</td>
<td>.244898</td>
<td>.434483</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>RAM</td>
<td>49</td>
<td>.9396888</td>
<td>1.33028</td>
<td>.00195</td>
<td>4</td>
</tr>
<tr>
<td>COLOR</td>
<td>49</td>
<td>13.02041</td>
<td>10.14168</td>
<td>4</td>
<td>32</td>
</tr>
<tr>
<td>HWCOST</td>
<td>49</td>
<td>1068.98</td>
<td>2054.781</td>
<td>20</td>
<td>900</td>
</tr>
<tr>
<td>QD</td>
<td>49</td>
<td>2.110204</td>
<td>2.032265</td>
<td>0</td>
<td>7</td>
</tr>
<tr>
<td>LOGP</td>
<td>49</td>
<td>4.810244</td>
<td>.4465414</td>
<td>3.89182</td>
<td>5.988961</td>
</tr>
<tr>
<td>LOGHW</td>
<td>49</td>
<td>5.590149</td>
<td>1.729714</td>
<td>2.995732</td>
<td>9.10498</td>
</tr>
<tr>
<td>TREND</td>
<td>49</td>
<td>6.020408</td>
<td>2.954444</td>
<td>0</td>
<td>10</td>
</tr>
</tbody>
</table>

Notes: The units of HWBASE and HWBASE are in millions of units. The units of CPU are in MHz. The units of RAM are in MB. The units of HWCOST are in dollars/MB. The units of QD are in millions of units demanded.
### 8.3 Table 3: Regression on Log Price

<table>
<thead>
<tr>
<th>LOG(PRICE)</th>
<th>base specification</th>
<th>specification with trend variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>HWSHARE</td>
<td>0.610* (0.334)</td>
<td>0.241** (0.119)</td>
</tr>
<tr>
<td>RAM</td>
<td>0.316* (0.161)</td>
<td>0.365** (0.128)</td>
</tr>
<tr>
<td>COLOR</td>
<td>0.074** (0.031)</td>
<td>0.076*** (0.019)</td>
</tr>
<tr>
<td>TREND</td>
<td>N/A</td>
<td>−0.113*** (0.014)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.267</td>
<td>0.712</td>
</tr>
<tr>
<td>Observations</td>
<td>49</td>
<td></td>
</tr>
</tbody>
</table>

Notes: White (1980) heteroskedasticity-robust standard errors are reported in parentheses below coefficient estimates. Significantly different from zero in a two-tailed t-test at the *ten percent level; **five percent level; ***one percent level.
### 8.4 Table 4: Regression on $Q^d$

<table>
<thead>
<tr>
<th>$Q^d$</th>
<th>standard regression</th>
<th>IV regression</th>
</tr>
</thead>
<tbody>
<tr>
<td>HWBASE</td>
<td>0.266*** (0.050)</td>
<td>0.332** (0.148)</td>
</tr>
<tr>
<td>PRICE</td>
<td>-0.014*** (0.003)</td>
<td>-0.111 (0.102)</td>
</tr>
<tr>
<td>CPU</td>
<td>-0.086 (0.057)</td>
<td>-0.395 (0.279)</td>
</tr>
<tr>
<td>RAM</td>
<td>2.410 (2.161)</td>
<td>9.690 (7.38)</td>
</tr>
<tr>
<td>COLOR</td>
<td>0.177 (0.161)</td>
<td>0.468 (0.503)</td>
</tr>
<tr>
<td>TREND</td>
<td>-1.047*** (0.141)</td>
<td>-2.560* (1.424)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.619</td>
<td>N/A</td>
</tr>
<tr>
<td>Observations</td>
<td>49</td>
<td>49</td>
</tr>
</tbody>
</table>

Notes: White (1980) heteroskedasticity-robust standard errors are reported in parentheses below coefficient estimates. Significantly different from zero in a two-tailed t-test at the *ten percent level; **five percent level; ***one percent level.