ABSTRACT

In the video game industry there is a general consensus that mainstreaming occurred in the period from the mid 1990’s to the present time of 2005. Using data that covers the period from 1995 to 2002, this paper examines empirically how the increase in casual gamers has affected the demand for games that provide time cost savings in purchasing decisions. Findings show that casual gamer demand increase was approximately 140 percent higher than that of hardcore gamer demand during this time. In response, software firms increased the supply of information shortcut games relative to other types of games.

Keywords: Video game industry economics, time costs, mainstreaming
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1. Introduction

“The video game industry has been on the threshold of seizing dominance in entertainment for several years. Ultimately, it will. It’s inevitable: we play games....There is a fundamental difference between movies and video games: the games are interactive, movies are passive. I don’t see any way out of this.” --syndicated columnist Bob Schwabach, The New York Times, May 13, 2001.

In the half-way mark of the 21st century, the video game industry has emerged as the fastest growing segment of the United States entertainment sector. According to market research company DFC Intelligence (2004), sales of video game hardware and software generated $23.2 billion worldwide in the year 2003, and in the United States alone software sales were reported at $7 billion, doubling revenue from 1996. But even as far back as 1999, the mainstream media began reporting that video game sales had surpassed that of the movie industry, and a report of that same year by the Interactive Digital Software Association gave other numbers: from 1997 to 2000 the industry grew at a clip of 15 percent per year, double the rate of the US economy; 60 percent of all Americans, or 145 million people, identified themselves as game players; and 215 million copies of software were purchased that year, which amounted to two games per each American household (IDSA 2001).

A large portion of the video game industry’s ascent up the entertainment hierarchy may be attributed to its enlarging of its consumer base. While Nintendo’s 8-bit Nintendo Entertainment System was thought to have been largely consumed by boys from ages 8 to 14 during the late ’80s, the game players of today’s generation are of a much broader age range. The average game player is listed as 29 old, and 17 percent of the game-playing population is reported as 50 years and over. Along with the greater spread in age, the video game industry has become more gender balanced to
the point where in 2003 it was estimated that 39 percent of the gamers were female (ESA 2004).

The industry’s growth in size and its simultaneous shift in consumer demographics presents a situation of economic interest. Past economic papers on the industry have mostly focused on the network effects of the video game industry to explain the supply and demand trends of video game hardware and software. What has yet to be covered is the effect that the change in consumer base has had on the demand of different types of video game software.

The video game press and Internet chat forums often state that this new wave of older and female gamers also tends to be more casual gamers who are not as dedicated to gaming as their teenage male counterparts, and as a result, they tend to buy games through different channels than their hardcore brethren. Specifically, while hardcore gamers are thought to scour video game magazines and rely on word of mouth for well-reviewed games, this growing group of casual gamers are thought to more likely buy games with license tie-ins to other familiar products such as a film, or buy a sequel of a proven game.

In light of this perspective, the objective of this paper is to test empirically if the increase in proportion of casual gamers from May 1995 to February 2002 increased the sales of license tie-in and sequel games. From a broader economic perspective, it is an investigation of how a change in consumer base to the mainstream affects the demand of products that seem better suited to provide savings on time costs.

The paper is divided so that the first section familiarizes the video game while discussing the literature review of that industry. Much of the previous economic
studies conducted on the video game industry involve network effects, and the section serves to connect the topics of network effects to the present question at hand while explaining the slightly different purposes of this particular paper.

The following sections are broken down to that of mainstreaming and information shortcuts. The section on mainstreaming discusses past papers on the film industry that study how branding in movies attracts mass audiences. Thereafter, the section presents evidence from several sources that suggest that mainstreaming has been occurring in the last decade or so due to purposeful attempts by video game firms to achieve this goal.

After that section establishes the presence of mainstreaming in the video game industry, the section on information shortcuts then links the effect of mainstreaming on time cost saving products. The literature in this section presents the superstar information cascade theories that are prevalent in the music and film industries. Subsequently, time cost savings in the video game industry is shown. The group of games that provide time cost savings are marked as “information shortcut” games, and they are analyzed in detail as to how they provide such time cost saving measures.

Following these three sections that show the relevance of mainstreaming and information shortcuts in the video game industry, the methodology part of the paper presents a product diffusion model that attempts to illustrate the impact of sales on games with time cost savings due to the increase in game demand composed of casual gamers.

A regression analysis of the theoretical model reveals that casual demand growth grew at a yearly rate that was 9.6 percent higher than that of the yearly growth
of hardcore game demand, and the overall yearly growth rate for casual gamers was approximately 16.55 percent. Analysis on the composition of games then shows that software firms have released time cost savings games with greater frequency in order to capitalize on the higher demand for such games.

2. The Video Game Industry

2.1 The Basic Structure of the Video Game Industry.

Before previous empirical studies on the video game industry can be discussed, the structure of the industry should be understood. The industry is divided into the three categories of hardware providers (Sony and its Playstation, Microsoft and its Xbox), software developers (Electronic Arts, Acclaim, etc.), and consumers. The hardware firms produce hardware (also referred to as platforms) that are sold directly to consumers, and they charge software developers license royalties to produce games that will function on the hardware. While software developers often produce games for multiple platforms, they will produce more games or even exclusively for the hardware they think will garner the most consumers. On a side note, it must be stated that hardware providers such as Nintendo have their own in-house software developing divisions to produce games for their own platform. As for the consumer, he or she must buy the hardware and software separately, but needs both in order to achieve a gaming experience.

The cycle of the video game hardware market functions so that in the beginning, one hardware provider releases a platform that receives the support of all software developers and consumers. Shortly after, other hardware providers enter the market.
with platforms that are not universally standardized with each other to form two-way, three-way, and sometimes four-way competition. This platform battle lasts for several years after which definite market winners arise. At the end of this platform “generation,” the losing hardware providers often fold and drop out of the industry while the winners develop more technologically advanced platforms to start a new generational competition in the platform market. The void left by the losers is filled with other hardware providers that enter this new generation, and the hardware cycle is repeated once more.

2.2 A Short History of the Home Video Game Industry

The platform that started the first generation of hardware battles was the Channel FDD that was released by the firm Fairchild in 1976. A company called Atari soon entered the market with a platform called the VCS. Armed with a popular game called *Home Pong*, the VCS won out the first generational competition of hardware and gave Atari the early edge in the video game market (Gallagher and Park 2002). Atari built upon this initial lead by providing other successful games such as *Space War* and *Pac Man* for its second generation platform Atari 5200, and by 1982 it had thwarted rival platforms to control 80 percent of the US video game industry (Kline, Witheford, Peuter 2003).

After video game sales reached a peak of $3 billion in 1982, a glut of slip-shod games and management miscalculations forced Atari, Mattel, and Coleco to abandon the market almost entirely by 1984. In the wake of the mass exodus, the Japanese company Nintendo entered the scene and resuscitated the moribund industry with its
U.S. launch of the Nintendo Entertainment System (NES) in 1986. The NES saw brisk sales throughout the mid to late ’80s, and by 1989 Nintendo reigned supreme over the toy business; 23 percent of the $11.4 billion dollars spent on toys that year was attributed to Nintendo products, and in the following year one out of every three American household had a Nintendo console (Sheff 1999).

Even Nintendo, however, could not maintain its dominant hold over the video game market. In 1989 the arcade game company Sega introduced the Sega Genesis. Technically superior to the NES, the Genesis built a large enough installed base that helped it to eat away at Nintendo’s market share even after Nintendo introduced the Super Nintendo in 1991 to combat the Genesis (Kent 2001). By 1995 when both the hardware cycles of the Genesis and the Super Nintendo were drawing to a close, the Genesis had slightly larger installed base over the Super Nintendo, 11.7 million units to 8 million, respectively (Shankar and Bayus 2003).

The competition between Sega and Nintendo in the 16-bit era of platforms was soon forgotten by the dominance of the Sony Playstation in the following generation. The electronics conglomerate Sony introduced the Playstation to the U.S. market in September of 1996, and after few years of competition with the Sega Saturn and the Nintendo 64, it pulled away as the clear winner of the 32-bit generation. Marketing aggressively to branch beyond the adolescent boy market for video games, Sony recorded total sales of 80 million Playstations sold by the year 2000 (Alvisi, Narduzzo, Zamarian 2003). After riding the Playstation over a successful run of five years, Sony released the Playstation 2 for the newest and current generation of video games (Kent 2001). During this current generation, the software giant Microsoft entered the video
game market with a platform called the Xbox and the veteran firm Nintendo released its latest hardware offering in, the Gamecube. While this hardware generation is yet to be completed, by 2003 it became clear that the market had already tipped in the direction of the Playstation 2, for it had already sold 24 million units to 8 million of its nearest competitor, the Xbox (Dukcevich 2003).

2.3 Literature Review of the Video Game Industry

Perhaps due to its relatively short history compared to its film and music industry cousins, the video game market has had little economic or business management papers analyzing the economic implications occurring in the industry. The few notable papers are divided into non-empirical studies that analyze the successes and failures of video game consoles and empirical studies that measure the network effects found in such a product. Of the first kind of study, Melissa Schilling (2003) gives several recommendations for a potential hardware company to consider before diving into the market. She suggests that an entrant should provide superior technology compared to the incumbent, and gives the example of how Sega Genesis’s 16-bit challenge to the 8-bit Nintendo wrested away the market in Sega’s favor. From the perspective of the incumbent, it is wise to market peripheral add-ons such as joysticks and memory cards so that the user may invest heavily on the hardware and find it difficult to switch to another console. Another strategic maneuver of the incumbent is to concentrate on building a large, initial installed base of users so that network effects will sustain the firm a competitive advantage over its rivals.
Gallagher and Park (2002) expound on a number of similar concepts as Schilling when analyzing the success and failures of video game consoles, but they base their analysis under the umbrella of an expansive historical context. In their paper they document the six generations of video game hardware competition that has occurred since the introduction of the very first home video game console in 1976.

While the competitive struggle of each generation is shown to have contributed to the evolution of video game technology and industry, the third and fifth generations stand out in their significance. Starting sometime in 1986, the third generation came in the heels of a video game industry implosion in which the poor marketing and managing decisions of Atari and its rivals left a vacuum. Nintendo swooped in and built its video game empire through a combination of rigorous control of its software quality and arm-twisting tactics of both its game publishers and distributors. Nintendo’s reign during this generation is classified by Gallagher and Park as an example in which a first mover with a well-structured network is able to dominate its market.

What is interesting about the video game industry is that often times the winner in the round of one generation is unable to sustain the momentum in successive generations. As dominant Nintendo was during its heydays of the late ’80s and early ’90s, by the time of the fifth generation of console wars it lost its crown to Sony. In this generation, the Sony Playstation came out as the winner by first establishing the CD-ROM as the preferred design over cartridges and then expanding its installed base by lowering the price of its core products; in 1995 the Playstation was offered at $299 compared to the $399 of its main rival Sega Saturn, and in 1996 Sony lowered the price again to $199 to overcome Sega in its market share of the 32-bit market.
As a conclusion of their historical analysis they find that there has been a lack of a clear, dominant design in the video game industry that has been maintained over the years, and such an absence prevented firms from building switching costs to their users. In order to establish such switching costs, Gallagher and Park theorize, like Schilling, that a console should concentrate on enlarging its network effects through a strong installed base and a set of appealing complementary products in the form of good software.

Such network effects, sometimes referred to as bandwagon effects, is defined by Jeffrey Rohlfs (2001) as a benefit that a person enjoys as a result of others’ doing the same thing that he or she does. Network effects can be achieved in both direct and indirect ways. On a direct level, the more users there are of a particular console, the easier it is for those users to swap games with one another, and the recent advent of head-to-head on-line gaming has added a new dimension to direct network effects of user satisfaction. The more substantial effects of network effects, however, is found at the indirect level. The more users there are of a particular platform, the more likely it is that game publishers will create more games for the platform, which in turn attracts more users and lengthens the longevity of the hardware.

Network effects is a highly relevant concept in the video game market and is explored by a couple of empirical papers. Shankar and Bayus (2002) divide network effects into network size, otherwise known as the installed user base, and network strength, which is viewed as the marginal impact of a unit increase in network size. They create a demand model for the two console firms of Sega and Nintendo in which the dependent variable is affected by the explanatory variables of the initial installed base (network size) and price-network and advertising-network of the console (network
strength). Their regressions show that the direct effect of network size was not significant at the 0.05 level, but that the difference between the two firms’ price-network size coefficients and advertising-network size coefficients were found to be significant and favorable to Nintendo.

Such findings indicate that Nintendo had a superior network strength to that of Sega so that holding installed base constant, if the two firms were to give the same price cuts on consoles or increase their advertising, Nintendo would attract more users to its console than the Sega Genesis. This conclusion is aligned with what actually took place during the battle of the two 16-bit consoles: In 1993 the Sega Genesis had twice the installed base of the Super Nintendo. Over the next two years, however, Nintendo spent more than Sega on advertising, and in 1995 the Super Nintendo sold more units than the Genesis. Shortly afterwards the 16-bit generation came to a close with the Genesis ending its run with a slightly larger installed base than the Super Nintendo, but the study suggests that had the hardware generation continued, the Super Nintendo would have eventually built a larger installed base. Shankar and Bayus reason that in light of such findings, a firm that starts off with lower network size will be able to play catch up if it has superior network strength.

Clements and Ohasi (2004) point out that Shankar and Bayus are mistaken in viewing network effects in the videogame market as direct network effects. They assert that in the video game industry, it is the indirect network effects of more games made available by a larger installed base that often determine the success of a console. In order to examine how this indirect network effects evolve over a console’s product cycle, they conduct an empirical study using hardware and software sales data for the period 1994 to
2002. They model consumers’ willingness to buy a certain console with the following utility equation:

\[ u_{jt} = \beta_0 + x_j \beta_x + \beta_p p_{jt} + \omega h (N_{gt}) + \xi_{jt} + \epsilon_{jt} \] (a)

\( u_{jt} \) = utility at time \( t \) by choosing console \( j \) among \( J_t + 1 \) alternatives

\( \beta_0 \) = constant

\( x_j \beta_x \) = average benefit from console technology

\( \beta_p p_{jt} \) = price of console \( j \) at time \( t \)

\( \omega h (N_{gt}) \) = number of game titles

\( \xi_{jt} \) = deviation from average benefit of console technology

\( \epsilon_{jt} \) = error term

Clements and Ohasi then transform this utility function into a two stage logit model that produces the following linear regression model:

\[ \ln (s_{jt}) - \ln (s_{0t}) = \beta_0 + x_j \beta_x + \beta_p p_{jt} + \omega h (N_{gt}) + \sigma \ln (s_j|B_t=1) + \xi_{jt} \] (b)

where \( s_{jt} \) is the share of the hardware market captured by console \( j \) during period \( t \), and \( s_{jt|B_t=1} \) is the console \( j \)’s market share given that consumers decide to purchase video games at period \( t \).

As a second part of this study on indirect network effects, Clements and Ohasi derive a model for the determining factors for the number of game titles available for a console. Their profit maximization model of software firms is beyond the scope of this paper and will not be presented, but the profit maximization equation is linearized into the regression equation:

\[ \ln (N_{jt}) = \alpha_j + \gamma \ln (IB_{gt}) + \eta_{jt} \] (c)

\( N_{jt} \) = number of game titles for console \( j \) at time \( t \)
$\alpha_j = \text{console fixed effect}$

$\text{IB}_{gt} = \text{cumulative sum of console sales up to the time } t-1$

$\eta_{jt} = \text{mean-zero error}$

Summarizing the two equations of (b) and (c), the theory behind equation (b) is that hardware share of the market increases with the drop of the hardware price and greater availability of software for it, whereas with equation (c) the testable theory is that number of titles that software firms release for a platform increases with increases in the installed base. When regressions are run on this equation, the study reveals that the yearly demand elasticity with respect to price by console was -2.58 on average. The elasticity was also estimated to be -4.55 in the first year of console’s introduction and increased with age until it reached -1.16 when the console had been out for seven years. As for the hardware elasticity of demand with respect to software availability, it was found to be at 1.82 on average but varied greatly among consoles.

The results of the software entry equation shows that holding a console’s age constant, a 1 percent increase in the installed base expands the software availability by 1.18 percent. Not surprisingly, results also show that holding the installed base size constant, software publishers produce less games for older consoles. Interestingly, the elasticities of software variety with respect to the installed base is revealed to be similar across consoles.

Clements and Ohasi conclude from their study that in the beginning stages of a console, the elasticity of hardware with respect to number of software availability is relatively low to that of console price. In the middle of the console cycle, however, the elasticity of software availability becomes greater before dropping off again at the end of
the console’s product life. In order for console firms to maximize their earnings, they recommend that aggressive penetration pricing be employed at the start of the product cycle while in the middle of the cycle hardware firms should lower royalties in order to encourage software publishers to make more games for their console.

While Clements and Ohasi conduct an extensive study on the indirect of network effects at the hardware level, they leave aside studies that might be performed regarding the software of video games. In their theory of network effects, they make the assumption that the consumer values all games equally while admitting that this is not an accurate depiction of reality; in fairness, their assumption of the homogenous quality of the software is of relatively little concern when studying the indirect network effects on hardware. However, beyond network effects, the shift in video game consumers to the mainstream presents possible opportunities of study of product changes due to changes in consumer demographics. It is of greater interest to observe the product changes in software rather than hardware due to the greater variety in software, and this paper will seek to differentiate between the consumer value of different types of games as will be shown in later sections.

3. Mainstreaming

3.1 Literature Review on Mainstreaming

In order to examine the economic effects mainstreaming has had on the videogame industry, it helps to observe the parallels of mainstreaming in the motion picture industry. In the film industry, there are several papers that investigate the impact branding has had on attracting mass audiences into theaters. In his historical analysis of
film branding, Bakker (2001) writes that as films became costlier to make during the 1910s, producers realized the need to brand the film as a marketing ploy. If potential movie watchers were able to receive preliminary information about the film through its brand, they would more likely watch that film over other non-branded films that offered no such information. Such branding techniques came in the form of casting bankable stars and making films based off of popular novels and plays. Whether the heavy investments made in paying lavish sums to movie stars and buying rights to novels were justifiable is reported by Bakker as an unresolved issue; surveys in 1929 and 1933 indicated that stars and stories were the main reason people went to the movies, but a correlation of .25 between stars and box office revenue was the best that studies could find regarding that time period.

DeVany and Walls (2002) expand on Bakker’s ideas of consumer desire to save on search costs and perform an empirical study on the impact of brand techniques in the period of 1985-96. They refine the theory by suggesting a non-informative information cascade situation in which consumers choose to follow leaders in choosing their product because they believe such leaders are more informed than they are or because they disregard their own preferences in order to follow the bandwagon. In the case of the film industry, this herd mentality can be capitalized upon by a “blockbuster strategy” of hiring well-known stars and advertising heavily in order to attract a large initial audience and snowball the film’s momentum into a mega hit.

Using data on 2,015 movies that were released during the ten year period of 1985-96, DeVany and Walls run regressions using the following model:
\[ \log \text{Revenue}_i = \beta_1 + \beta_2 \log \text{Budget}_i + \beta_3 \text{Star}_i + \beta_4 \log \text{Screens}_i + \beta_5 \text{Sequel}_i + \Gamma'[\text{Genre, Rating, Year}] + \mu_i \]

where \( i \) indexes movies and \( \Gamma \) is a row vector of parameters that account for variables regarding genres, ratings, and year of release.

For the blockbuster indicators of budget, number of opening screens, and stars, all are shown to be significant at least at the 5 percent level, but when broken down to deciles on the effects of box-office gross, it is revealed that these variables raise the lower deciles but hardly affect the upper decile revenues. This leads DeVany and Walls to believe that the blockbuster strategy may often put a higher floor for a movie’s box-office gross, but beyond this security net it cannot secure a sustained success at the box office. Interestingly, the variable of sequel is shown to decrease the lower decile of revenue while raising the revenues of the median and upper deciles. DeVany and Walls explain this trend by suggesting that since sequels are facsimiles of movies that have done well at the box-office in the past, they will reap the benefits of such an endowment. However, despite the higher earnings of sequels in the upper deciles of revenue, it should be noted that due to higher budget costs and lower revenue relative to the original, higher grosses for sequels do not necessarily translate to higher profits.

As a consequence of the findings, DeVany and Walls conclude that while the reliance of consumers on information short cuts leads to initial high returns for movies employing the blockbuster strategy, in the long run the word-of-mouth exchange between consumers and movie reviews by critics diminishes the effect of such search cost-lowering attempts. This result is important in that the video game industry exhibits similar blockbuster strategies, but the release of games are not accompanied with the same fanfare as the openings of movies. If the conclusion that word-of-mouth exchange
eventually mitigates the effect of search cost-lowering techniques also applies in the video game industry, it may be that the search cost techniques have a much lower impact there than in the film industry due to the lower levels of initial advertising and marketing for the game than the film.

Ravid (1999) conducts an empirical study with many of the same variables found in DeVany and Walls’s paper, but Ravid paints a much more detailed and comprehensive picture of the quality signaling associated with many of the measures. Regarding movie stars, the study finds that stars are unable to add to the profitability of the film due to the expensive salaries that they command, but they are able to generate higher revenues for films, indicating that they do have some signaling power to consumers. Likewise, regarding sequels, the sequel’s role in providing search cost savings is that it signals to the consumer that its predecessor was successful enough to warrant a sequel, and therefore hopefully, the sequel itself will provide an enjoyable experience.

Ravid’s study does find that sequels brought back higher revenues than non-sequel films. What is surprising is that positive or non-negative reviews of the film seem to either have no effect or be negatively related to revenues or returns on investments. This finding seems to contradict DeVany and Walls’s belief that good films are able to break out of the non-informative information cascade. Yet at the same time, Ravid’s study does not break down the results into deciles like that of DeVany and Walls, and so it is unwarranted to say that the two are same studies with different results. Also, it can be argued that critics’ reviews is a dubious proxy for the word-of-mouth between movie goers, and so a negative return to revenues despite favorable reviews does not necessarily
mean that movie-goers maintain their herd mentality throughout the duration of a film’s

cycle at the theater.

3.2 Mainstreaming in the Video Game Industry

Similar to the branding techniques exhibited in the film industry, in the last
decade or so the video game industry has made conscious efforts in reaching out to larger
audiences beyond its initial niche consumer base of pre-teenage boys. In the ’80s,
Nintendo catered to the market of adolescent boys of 8 to 14; Peter Main, vice-president
of Nintendo, headed a marketing team that launched a blitzkrieg of commercials,
magazines, and toy booths that marketed the Nintendo Entertainment System as the must-
have toy for boys (Sheff 1999). When Sega chose to enter the console foray in the
early ’90s with its 16 bit offering of the Sega Genesis, it sought to gain the loyalty of
older teenage boys as a product differentiating tactic. Armed with marketing campaigns
such as the “Sega Scream” that debuted on programs like the MTV Music Awards, Sega
touted its platform as a product for cooler kids in tune with pop culture (Kline, Witheford,
Peuter 2003).

Sony took note of Sega’s marketing triumphs and decided to one-up Sega for its
marketing of the Playstation. Instead of merely advertising to an older demographic,
Sony sought to broaden the video game playing audience by targeting a wider age range
of 12 to 24. Beyond enlarging the age group of its consumers, Sony reached for a more
sophisticated population than the original video game nerds by initially choosing to sell
the Playstation in music and electronics stores rather than video game shops (Alvisi,
Narduzzo, Zamarian 2003). The games themselves were notably more attractive to
mainstream consumers; Sony’s second-party developer Psygnosis was applauded for introducing techno beats to its game *WipeOut*.

This conscious, multi-pronged marketing campaign resulted in an eventual rise of what is now known as the “Playstation Generation.” The Playstation Generation was characterized by players who began playing video games with the introduction of the Playstation. They were older, hipper, less dedicated to the games than the Nintendo kiddies of the past, and they generally considered video games as another entry in the menu of entertainment choices. Less dedicated to gaming they may be, the Playstation Generation proved to be a dependable army in Sony’s quest for video game domination, as evidenced by the Playstation’s commercial success.

The development of this mainstreaming has led the industry to divide its consumers into the groupings of hardcore and casual gamers, and Morris (2004) estimates that hardcore gamers constitute 20-25 percent of the market. Despite the liberal use of the words “hardcore” and “casual” in the industry, formal definitions of the two terms have yet to be defined. From an ideal economic perspective, it would seem that video game players would be surveyed as to their willingness to pay for video games, and a line would be drawn at some point to create the division. There is no such data on the video game industry, but Dave Rosen, one of the project managers at the largest software developer, Electronic Arts, states in an interview that Electronic Arts separates hardcore gamers and casual gamers based on the number of hours played and the type of games played (2004).

Ip and Adams (2002) attempt to create a crisper distinction between hardcore and casual gamers by listing out several characteristics of hardcore gamers and then placing a
weight on the importance of the characteristics on judging the level of gaming dedication. Of the 15 traits that they list, Ip and Adams assert that it is the factors of playing games over long sessions, discussing games with friends and on bulletin boards, and displaying comparative knowledge of the industry that are the top three signs of a hardcore gamer.

All three attributes demand a significant investment of time to video games, and if they are the telltale distinctions of a hardcore gamer, it would seem that an increased proportion of older gamers would indicate that the proportion of hardcore gamers is decreasing. Older gamers—gamers beyond the teenage years—are thought to have responsibilities such as jobs and families that give them less time for such gaming dedication, and as mentioned earlier in the paper, the industry’s gradual marketing reach to more mature audiences has brought in a larger group of these older gamers; separate from the Entertainment Software Association’s finding that the mean age of the gamer is now close to 30 years of age, the market research company IDC reports from their own survey that 36 percent of gamers are now over the age of 25 (Olhava 2004). This increase in older gamers, however, may not be merely due to shift in marketing tactics by game firms. Ryoichi Hasegawa, an industry veteran of Sony, points out that gamers grow older alongside the cycle of a platform, and recent platforms such as the Playstation have begun to have longer lifecycles than in previous generations. He believes that as the gamers age, new constraints on time transform hardcore gamers to casual gamers with less dedication and more conservative tastes (Stevenson and Berkowitz 2004).

Besides the increasing number of older gamers, the increased number of females playing games is thought to be another influence in the rise of casual gamers in the industry. For much of its history, the video game industry’s roots in the military had
given it a masculine slant that kept women at bay. In the height of the Cold War during the late 1950s, military funding made its way to academic institutions in order to expedite the research of computer science technology for nuclear mobilization and space exploration. At MIT, an artificial intelligence department was established, from which real-time and mini computers such as the Programmable Data Processor-I (PDP-I) were developed. It was in 1961 that an MIT student named Steve Russell created Spacewar on the PDP-I, and since then the software of videogames has been dominated by a tradition of games that require the destruction of objects in order to complete a mission (Kline, Witheford, Peuter 2003). Due to this masculine objective, female gamers comprised a very small population of the gaming industry during the ’80s (Sheff 1999), and the few girls who did venture into this male virtual world were thought to be siblings of adolescent boys and were secondary gamers who spent little time playing them.

Again however, new aims of the industry during the 1990s to branch out beyond the adolescent boy demographic has resulted in bringing in more females to the industry. In an interview, Brenda Laurel, founder of the girl game company Purple Moon Company, confirms that throughout this decade the proportion of female gamers increased steadily from less than 10 percent in the early ’90s to about 25 percent by mid-decade (2004), and ESA research shows that 39 percent of gamers are now female, up 30 percent from 1996.

Even as the proportion of female gamers rise, the consensus in the industry is that females are often casual gamers rather than the hardcore gamers who invest heavily on games. Shelley Olhava of IDC states that “the proportion of secondary female gamers is almost more than double the proportion of female primary gamers across platforms

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“Olhava 2004.” This finding leads to the conclusion that there are more sisters and mothers playing the games than ever before, but they remain as less interested gamers than the males in the household; this further enhances the theory that the proportion of casual gamers have increased in the video game industry.

4. Information Shortcuts

4.1 The Literature Review on Time Cost Saving Measures

As shown, the general agreement in the video game industry is that the proportion of casual gamers has increased, but the implications of this increase in the video game market, namely on the software market, have yet to be fully explored. As discussed thus far in this paper, the distinction between hardcore and casual gamers is that casual gamers are less likely to invest time on playing games. Since casual gamers have less time allocated for video gaming, in a sense it is more costly for casual gamers to spend time trying to find the suitable game compared to the hardcore gamer. As a result, it would seem that an increase in casual gamers would result in an increase of games that somehow provide time cost saving measures due to factors unrelated to the content itself, such as recognizable brand tie-in with a popular film.

The concept of consumer congregation around a time cost-saving product has an economic literature that dates back to Sherwin Rosen’s (1981) paper on the superstar theory. Coining the phrase “the phenomenon of superstars” for scenarios in which a relatively small number of people earn large wages for the activity they engage in, Rosen noted that such a superstar phenomenon was likely to occur when imperfect substitution prevented lesser talent from being substitutable for greater talent and when costs of
production did not rise in proportion to the size of the demand market. As Rosen concludes his paper, he highlights the tenor singer Pavarotti as an example in which a once-in-a-lifetime talent is able to reap a commanding salary due to his unique voice and the ability of the radio and phonograph records to duplicate his performance at a relatively small marginal cost.

Adler (1985) builds upon Rosen’s theory of the superstar phenomenon, but he dismisses Rosen’s original insistence that imperfect substitution of talent is a contributing factor in skewness of earnings. Rather, he theorizes that the phenomenon of superstar exists where consumption requires knowledge, and in such a market, the resulting star need not possess a greater talent than his or her competitors. A simple model of this is proved in the following:

Suppose there are two artists of equal talent, and \( x \) and \( y \) are the units of time consumers devote to the art produced by them (by devotion to art, Adler means both time actually spent in direct contact with the art and in discussing the art with other individuals). A utility function can then be mapped out:

\[
U(x, y) = u(x, 0) + u(0, y)
\]

In this equation \( u \) has only one parameter so that \( u = u(\nu) \) and \( \nu = x, y \). Since the two artists are thought to be of equal talent, \( x = y, u(x) = u(y) \). Adler states that enjoyment increases with knowledge, and therefore the marginal utility is increasing: \( u' > 0, u'' > 0 \).

The consumer will choose to listen to either both artists or one of the artists based on the cost. The cost of consumption is simply time and is divided into time spent on the art and time searching for an artist the individual can discuss with others. The search
time is \( I/X \) and \( I/Y \) where the capital letters indicate the total number of consumers who choose the corresponding artist. The budget constraint of the consumer is then

\[
x(1 + 1/X) + y(1 + 1/Y) = I
\]

where \( I \) is the total units of time the consumer devotes to art and the search involved. If \( X = Y \), the consumer will be indifferent between devoting his time to the artists, but if more of other consumers choose \( x, X > Y \), and the consumer is better off consuming \( x \) as depicted in the indifference map below:

Adler’s theory can be summarized as such: in certain markets such as the music industry, potential consumers initially face the dilemma of choosing an artist to listen to. They are assumed to derive enjoyment both from listening to the music and from discussing the music with other listeners. Since the costs incurred in engaging in these activities are the time costs of time spent listening to the music and time spent searching for others to discuss the music with, consumers choose to patronize the most popular
artist in order to save on the latter search cost. Adler argues that such a consumer behavior pattern leaves the artist’s talent out of the equation, and it is by factors such as initial media exposure that decides which artists become superstars.

While a direct study testing Adler’s theory of consumer behavior in the video game industry has yet to be carried out, such empirical studies do exist regarding the music industry. Hamlen (1991) presents a study in which he specifically tests Adler’s theory that talent does not matter in an artist’s ascension to fame and fortune. Using data from the period 1955 through 1987, Hamlen regresses the dependent variable record sales on the independent variable voice quality while controlling for other factors such as gender, race, and genre of music. The results of the study show that consumers do recognize the voice quality of the singer but the cross elasticity of record sales due to voice quality is 14.2 percent and considered too small an effect by Hamlen, and therefore, he upholds Adler’s view of the insignificance of talent over Rosen’s theory.

Crain and Tollison (2002) regard Hamlen’s use of voice quality as measure of artist talent to be too subjective and limiting to adequately cover the superstar phenomenon in the music industry, and so they conduct their own empirical study. In their research they concentrate on testing Adler’s theory of consumer’s desire to find a star to listen to as soon as possible, and their resultant empirical model regresses artist concentration on explanatory variables such as teenage share of population and death rate of active duty military while controlling for factors such as music variety. The regression results of the study support their hypothesis that longer expected time horizons did in fact increase artist concentration, hinting that Adler’s theory carries merit. However, some of the variables used as evidence of their case seem to stretch the bounds of plausible
connection to artist concentration; the notion that a higher death rate of active duty
military lowers expected time horizons and subsequently lowers the value of selecting
artists favored by other consumers seems a bit of a stretched argument.

4.2 Information Shortcut Games in the Video Game Industry

The music industry studies on the superstar theory are relevant to this paper in
that they discuss time cost savings, but it is a theory that suggests that consumers choose
to consum the most popular product in order to save on the search costs of finding others
with whom to discuss the product with. In that regard, the superstar theory would be a
better explanation of why hardcore gamers latch on to the same type of games, for it is
the hardcore gamers who are more likely to want to discuss the game with friends at the
school playground or Internet chat forums.

Therefore, slightly different from the superstar theory, the casual gamers does not
wish to save time in finding the right community to discuss the product with, but rather
they want to save on the search cost of finding a product of suitable taste; in such logic,
the popular product serves in the consumers’ minds as a proxy for superior quality. Like
the movies that rely on bankable stars to sell tickets to the mainstream audience, there
seem to be games with signaling mechanisms to attract the casual gamer. For the
purposes of this paper, such games that carry these branding techniques are called
“information shortcut games” in that without having played the game, consumers are able
to gather some information of the game’s content due to its external characteristics.
Specifically, games with tie-in to sports leagues or sports stars, games with license tie-ins
to movies or other products such as TV shows and board games, and sequel games are presented as the three different types of information shortcut games.

For film and TV license games, casual gamers who know very little about games but are aware of film and TV culture will be signaled to the content of the game, but these license tie-in games are also likely to have a high casual gamer constituency due to their poor reputation with the better informed hardcore gamers. Movie license tie-in games have had a checkered history since the failure of the game *E.T.* Hoping to cash in on the popularity of the film, Atari rushed the game to the shelves in time for the holiday season of 1982 only to see it remain there due to its poor quality (Phan 2004). The weak sales of *E.T.* was partly blamed for the bankruptcy of Atari, and thereafter joint ventures between Hollywood and video games were largely put aside until a second wave of attempts was made starting some time in 1994. During this time CD-ROM technology began to appear in video game platforms, and it allowed for full motion in games that inspired game developers to create “interactive films” for the gamer. However, this blend of the movie and the game created for an unsatisfactory experience, and it further cemented the industry belief that games and films should remain as separate entities.

Since then, the success of the James Bond-inspired game *Goldeneye* has induced game firms to continue to produce movie-licensed games (Kent 2001), and recent releases of film-based games such as *Spiderman 2* and *Chronicles of Riddick* have been well-reviewed by video game critics as well as finding commercial success. However, in the hardcore community, the film and TV license tie-in games have not quite escaped the stigma of being inferior products, and these license tie-in games remain as purchases of casual gamers.
Just as film, TV, board game, and other license tie-in games are more likely to attract the casual gamer, games with sports league tie-ins also provide information shortcuts for the casual gamer. In video game lore, the software firm Electronic Arts is attributed for its successful recruitment of sports fans to the video game industry through its development of the game *John Madden Football*. Started up in 1982 by Trip Hawkins, Electronic Arts (EA) published its first version of *John Madden Football* for the Apple II computer in 1986 (Kent 2001). The game proved to be a success, but it was only when the game was converted to the Sega Genesis with faster gameplay that *John Madden* became synonymous with video game football. With the introduction of the Playstation and its graphical capabilities, game designers were able to create much more realistic digital renderings of athletes. The more life-like depictions of the sports experience has been credited with bringing in sports fans who otherwise would not play video games. The popularity of sports games has generally climbed throughout the last decade, and in 2003, seven of the top 100 selling games alone were reported to be National Football League tie-in games (Arrington 2003).

The third type of game, the sequel, is yet another information shortcut game that can be theorized to have gained popularity with the increased proportion of casual gamers. The production of sequels of top-selling games has always existed to a degree in the video game market; one of Nintendo’s mascot characters, Mario, has starred in numerous sequels as well as making guest appearances in other Nintendo games. However, sequels came to comprise a large share of the software market especially in the last decade as Sony and its contracted software developers cultivated multiple sequels for the Playstation’s most popular games such as *Metal Gear Solid, Tekken*, and *Gran Turismo*. 
This trend of creating such franchise line-ups has come to a point where in the holiday season of 2004, the most popular games were all sequels such as *Grand Theft Auto: San Andreas* and *Halo 2* (Herold 2004).

Ideally, all three types of information shortcut games should be equal indicators of content to casual gamers, but in reality we expect them to be unequal in their sensitivity to the changes in the fraction of game demand comprised of casual gamers. For the sake of simplicity, this fraction of game demand by the casual proportion of the consumer base is assigned the symbol $\delta$. As $\delta$ increases, the increase in sales of information shortcut games should be higher than that of non-information shortcut games, and that increase should be equal for sports-license, film-license, and sequel games.

However, the impact of the increase in $\delta$ varies across these three categories because the demand of the hardcore gamers for these games ranges as well. To be more specific, as stated earlier, film-license games have a poor reputation with hardcore gamers, and therefore the hardcore game demand $(1-\delta)$ for film games is likely to be lower than that of the other two information shortcut categories. In comparing sports license games and sequels, it is difficult to determine which type has greater hardcore game demand. On one hand sports license games attract hardcore gamers who want the detailed realism and athlete statistics that sports league licenses provide, but on the other side, some sequels of games that are violent or strategy-intensive can be thought to be sustained primarily by hardcore game demand. Yet, since it is not necessarily clear what aspects of a game (violence, strategy intensive, etc.) attract the hardcore gaming audience, we assume that hardcore game demand for sequels is between that of sports games and
film games. The impact of $\delta$ on sales of these types of games in relation to the “noise” of hardcore demand is depicted below:

5. The Model of Casual Gamers in the Video Game Industry

5.1 Literature Review of Product Diffusion

The model that will best answer the hypothesis of this paper is a product diffusion model that accounts for the unique market characteristics of the video game industry. Before drawing up such a model, however, a short literature on product diffusion is presented here to give the historical backdrop for such models:

Economic studies on product diffusion can be found as far back as 1957 when Zvi Griliches conducted his study on the diffusion of hybrid corn in the 1930s. Hybrid corn was a method of breeding superior corn in adaptable environments, and during the 1930s
the use of hybrid corn spread throughout the Corn Belt and it is outlying areas. In his study, Griliches applies a logistical growth curve model on the data of hybrid corn production in states and corn reporting districts to determine the rate of adoption of hybrid corn techniques by farmers.

Griliches’s logistical function reads $P = \frac{K}{1 + e^{-(a+bt)}}$ where $P$ is the percentage planted with hybrid seed, $K$ the ceiling value, $t$ the time variable, $b$ the rate of growth efficient, and $a$ the constant of integration which positions the curve on the time scale. After linearizing the equation, Griliches performs regression analysis on the model to find that the hybrid corn was adapted earliest in the Corn Belt states of the Midwest, and the rate of adoption was also higher in these states than in the Southern states of comparison. What is more, the ceiling of in the adoption of hybrid corn was higher in the Corn Belt so that in states such as Iowa and Wisconsin hybrid corn made up close to 100 percent of the total corn acreage planted while in Southern states such as Texas and Alabama, the ceiling levels did not reach even up to 80 percent.

Griliches explains this phenomenon by arguing that hybrid corn was much more aggressively marketed in the Corn Belt compared to the Southern states. He writes that in almost 90 percent of all the seed in the Corn Belt was sold by individual salesmen who came directly to the farmer, while in the South almost all the seed had to be bought at the store. Along with this inconvenience, Griliches also notes that certain characteristics of farming in the South such as the small size of corn acreage per farm, the relative isolation of the small farm, and large proportion of corn on noncommercial farms made it expensive to market hybrid corn in this area.
In another study of product diffusion in the agricultural industry, Paul David presents a paper on the motives for the mechanization of the reaping process in the antebellum Midwest (1966). Cyrus H. McCormick is credited for having invented the mechanized reaper in the 1830s, and his invention aided the small farmer in increasing the productivity of the farm. However, David raises the question as to whether the reaper was adopted throughout the Midwest region because farmers realized that expansion of the acreage of wheat sown per farm would increase profits or because mechanical reapers were substitutes for the grain cradle that would alleviate the scarcity of labor that restricted wheat production. Through his investigation, David comes to the conclusion that both theories are part of a single story of the effect of higher grain prices: The rise of grain prices in the 1850s induced farmers to increase their farm acreage to meet this demand while at the same time the higher grain prices drove up the farm wage rate relative to the cost of harvesting machinery, and both scenarios made the mechanical reaper more attractive to the farmer.

Since the reaper has greater fixed costs but lower marginal costs relative to hand labor, the average total cost of mechanized reaping would continue to fall even as the average total cost of the hand method would begin to rise. Thus, there is a certain threshold level of farm acreage size in which the farmer should switch to the mechanical reaper. David argues that in 1848 the average farm size and price of labor worked against the widespread adoption of the mechanical reaper, but by 1859 the enlargement of farm size and the increase in labor wages induced by higher grain prices had created a ripe situation for the reaper to diffuse rapidly throughout Midwest farms.
In David’s study, the adoption of the reaper was based on the farmers’ incentives for purchasing the product based on their farm size and factor prices. Alternatively, a paper by Dranove and Gandal present another diffusion study in which consumer incentives are dictated by the consumers’ desire to choose the winning product when the outcome of competition between products is uncertain (2003). Fast forwarding a century and a half since the days of the mechanical reaper, the study focuses on the adoption of the DVD player under threat of competition from DIVX players. An acronym for digital video disc, the DVD was presented into the consumer market in early 1997 to serve as a replacement for the VHS-format videocassette tapes. A year after its release, however, the electronic retail firm Circuit City released the DIVX, which was to play the same DVDs that DVD players could play while providing additional features. Since DVD players had yet to be openly embraced by mainstream consumers, the short-lived DIVX may have had an adverse effect in stalling the diffusion of the DVD player.

Dranove and Gandal conduct an empirical study to determine whether DIVX slowed the adoption process of the DVD format. They regress the natural log of the sales of DVD players on the variables natural log of price, software availability, percent of U.S. box office top 100 films released on DVD, and the different dummy variables accounting for DIVX presence in the market while controlling for seasonality. Their findings suggest that the preannouncement of DIVX had an adverse effect on DVD hardware sales. Dranove and Gandal show that in the fourth quarter of 1997, right after the future release of DIVX was announced, DVD sales declined, while in the year after, when it became apparent that DVD was the clear winner against DIVX, DVD sales rose dramatically throughout the fourth quarter. Along with this fact, an instrumental variable estimation
that they run on the equation shows that the preannouncement of DIVX reduced DVD sales by 20 percent. Eventually, DVD overcame this initial hiccup to become the successor to VHS, but the study demonstrates the difficulty of product diffusion when consumers are uncertain as to outcome of competition for a de facto standard.

5.2 The Functional Form for Game Diffusion

In creating the model of game diffusion, we start off with the functional form:

\[ y = f(\delta, IS, comp, IB, season, qual) \]

\( y \) = sale of game \( s \)
\( \delta \) = fraction of game demand comprised of casual gamers
\( IS \) = whether the game is an information shortcut game or not
\( Comp. \) = competition of other games out on the same platform
\( IB \) = installed base—cumulative hardware units sold
\( Season \) = seasonality
\( Qual \) = quality of the game

A discussion of each of these variables is presented later in this section, but the variables of main interest in affecting \( y \) are the variables of \( \delta \) and \( IS \). Pairing down the functional form to \( y = f(\delta, IS) \), the argument of the paper is reflected in that \( y \) should be equal or lower for information shortcut games than non-information shortcut games at initial values of \( \delta \), but as \( \delta \) increases, \( y \) values for information shortcut games widen. A possible divergence pattern between the two types of games is illustrated below:
The remaining question in this model of casual gamer is of how to measure the casual gaming metric $\delta$. As stated earlier in the paper, there is no accepted, formal definition in the industry for casual game demand, but the fact that $\delta$ has been argued to have steadily increased in recent years makes it suitable for time $t$ to substitute in as a proxy for $\delta$.

But if the variable $t$ is to be established as a proxy for $\delta$, we must account for the fact that $\delta$ rises in other subsets of time within the larger time period of 1995 to 2002. To explain more in detail, the video game market operates in a way such that more casual gamers buy a game later in its product cycle. Casual gamers also are thought to buy a platform later than hardcore gamers because they are willing to wait for the platform to drop in price, and they also are more willing to wait until all or most of the platforms of a generation have been released before deciding which hardware to buy. In these three components of game, platform, and generation time, there is a similar pattern in that less dedicated gamers will consume the product later in time, but this buying trend is
unrelated to the hypothesis that there has been a fundamental increase in overall casual gamer demand from 1994 to 2002. Therefore, in the regression equation shown later, variables for game, platform, and generation time are added on in order to isolate the effect of overall time increase on $\delta$.

Beyond these controls for late casual gaming entry, other control variables are necessary to make $t$ as accurate a proxy for $\delta$ as possible. In the functional form $y = f(\delta, IS, \text{comp}, IB, \text{season}, \text{qual})$, $y$ measures the sales of the individual game $s$ rather than the aggregate sales of games. As time goes on, other games are expected to enter the market to expand the game choices available, and this increased competition will lower the demand of game $s$. It is necessary to separate out this negative effect on $y$ as $t$ increases because it is unrelated to casual gamer demand. To isolate out this lowering of demand due to greater game competition, we insert into the regression equation the control variables of (a) the number of games available at time $t$ on platform $p$ that are of the same type as game $s$ (sports, sequel, non-information shortcut game, etc.) as well as (b) the total number of games available at time $t$ on platform $p$.

Adding in these two control variables solves the issue of $t$ being just a measurement of $\delta$, but these control variables might be endogenous in that game firms will release more games into the market as the number of gamers expands. To resolve this endogeneity, the control variable “installed base of platform $p$” (the number of hardware units sold) is added in to the equation. Adding the variable of installed base not only accounts for endogeneity of number of games available on the market, but it also controls for another factor associated with time $t$: As time $t$ increases, the installed base of platform $p$ increases, and with this increase in potential buyers for game $s$, the demand
for game $s$ will go up. One consideration of this installed base variable is that there may be network effects that increases game $s$ demand higher than expected; at basic logic, we would suspect that a 1 percent increase in the installed base will increase the sales of a game by 1 percent or lower. However, it is possible that the sales of a game may increase by more than 1 percent with network effects because the larger the gaming community becomes, the more information is disseminated among gamers, and as a result of gamers being better informed, software publishers will be pushed into making games with superior content. The combination of gamers’ enhanced knowledge and enthusiasm for games along with better games in the market would result in a demand increase of available games that is above the one-to-one ratio of hardware to software demand.

The final control that is needed in the equation is a variable that needs to control for seasonality. Despite the fact that the video game industry has expanded out of the toy market, video games still serve as Christmas presents, and therefore there are sharp spikes in the sales of video games during the fourth quarter of the year that need to be controlled.

The one variable that is not controlled for is the quality of the game. Certainly we would suspect that the quality of the game would affect its sales, but the subjective nature of discerning quality makes it difficult to add into the regression equation. The most viable option would be to judge quality based on the reviews of video game magazines, but even this route has its problems such as a high turnover rate of magazine reviewers, possible bias of the reviewers towards certain types of games, and lack of reviews for
earlier games in the sample. Instead of undertaking this messy task of rating games, the quality measurement is left in the error term in the regression equations.

The quick summary of the transformation of $\delta$ to $t$ with various control variables is that time $t$ is argued to be an adequate proxy for game demand comprised of casual gamers once the other effects measured in $t$ are controlled for. These other effects are the tendencies of casual gamers to enter the market at later stages of time, the decrease in demand because of other game options, and increase in demand due to a larger installed base. The variables of game time, platform time, generation time, number of games that are of same type, total number of games, installed base, and fourth quarter are added to control for all the necessary factors. The regression equation is presented in the following section.

5.3 The Regression Equation

In transforming the functional form to a regression equation, we present the following equation:

$$
\ln \text{sales}_{s,p,t} = \beta_0 + \beta_1 4th + \beta_2 \text{time} + \beta_3 \text{gen} + \beta_4 \text{plat} + \beta_5 \text{game} + \beta_6 \ln \text{type} + \beta_7 \ln \text{total} + \beta_8 \ln \text{IB} + \beta_9 \text{IS} + \beta_{10} \text{time*IS} + \beta_{11} \text{gen*IS} + \beta_{12} \text{plat*IS} + \beta_{13} \text{game*IS} + u
$$

(1)

where

$$\ln \text{sales}_{s,p,t}$$: The natural log of sales of game $s$ for platform $p$ at month $t$. Sales are adjusted for inflation and are presented at 1995 dollars. The natural log of sales is taken because it is often standard procedure to take the logarithmic form of dollar amounts.

Applying the logarithmic form will eliminate or at least mitigate any skewness or

* Another variable that affects the sales of game $s$ is the price of the game, but we assume in this paper that the price of games are uniform and stay constant throughout the game’s life cycle.
heteroskedasticity that might be present in a strictly positive form of game sales. It should be noted that game sale observations is presented as a flow variable and accounts for sales of a game \( s \) for each month rather than cumulative sales of the game.

\( \beta_0 \): The constant.

\( 4th \): A dummy variable that accounts for the months of October through December of each year to control seasonality of sales.

\( Time \): Overall time. The variable is measured by the number of months since May 1995.

\( Gen \): Generation time. Since there are only two generations in the data set with the 32-bit encompassing the majority of the entries, generation time is measured as the number of other platforms that are out in the generation besides platform \( p \) in order to avoid strong multicollinearity with overall time.

\( Plat \): Platform time. The variable is measured by the number of months since platform \( p \) is released.

\( Game \): Game time. The variable is measured by the number of months since game \( s \) is released.

\( Ln \text{ type} \): Natural log of the number of games available at time \( t \) on platform \( p \) that are of the same type as game \( s \). In this equation, a game is separated as either an information shortcut game or a non-information shortcut game, and so there are only two type of games available at a given time.

\( Ln \text{ total} \): Natural log of the total number of games available at time \( t \) on platform \( p \).
\textit{Ln IB}: Natural log of the installed base at a time \( t \) on platform \( p \). Installed base is measured by cumulative number of hardware units sold up that point.*

The coefficients for \textit{type}, \textit{total}, and \textit{IB} are presented in natural log form for a particular reason: The dependent variable is the sales of individual game \( s \), but we are more concerned with the aggregate demand of the software market for a platform. Arithmetically, this aggregate variable is \( \ln \left( \frac{\text{total} \cdot \text{type} \cdot \text{sales}_{s,p,t}}{\text{IB}} \right) \) compared to the individual variable of \( \ln \text{sales}_{s,p,t} \). Using the rules for natural log, however, we can transform the aggregate equation to regression equation 1 as demonstrated in the following steps:

\[
\ln \left( \frac{\text{total} \cdot \text{type} \cdot \text{sales}_{s,p,t}}{\text{IB}} \right) = \beta_0 + \beta_1 4^{th} \ldots \quad \text{aggregate regression equation}
\]

\[
\ln \text{total} + \ln \text{type} + \ln \text{sales}_{s,p,t} - \ln \text{IB} = \beta_0 + \beta_1 4^{th} \ldots \quad \text{log rules applied on left side}
\]

\[
\ln \text{sales}_{s,p,t} = \beta_0 + \beta_1 4^{th} \ldots - \beta_6 \ln \text{total} - \beta_7 \ln \text{type} + \beta_8 \ln \text{IB} \ldots \quad \text{same as equation 1}
\]

Hence, the variables of \textit{total}, \textit{type}, and \textit{IB}, are not only presented in natural log form, the coefficients for \( \ln \text{total} \) and \( \ln \text{type} \) are expected to be negative, while the coefficient for \( \ln \text{IB} \) should show up as positive.

\textit{IS}: Dummy variable for information-shortcut game. The variable is given 1 for all games that have sports licenses, other licenses mostly in the form of film licenses but also licenses such as TV and board game licenses, and sequels.

\textit{Time*IS, gen*IS, plat*IS, game*IS}: The interaction terms between the four different time dimensions and the dummy variable for information-shortcut games.

* Note that coefficients \( \beta_6, \beta_8 \) are presented as stock rather than flow variables and show cumulative figures.
$u$: Error term. As discussed in the previous section, the quality of the game is one of the variables placed in the error term due to the difficulty of judging the content of a game.

5.4 Data

The data used for regression analysis was donated generously by Matt Clements. It reports the monthly sales figures of games of seven different platforms from May 1995 to February 2002. The seven platforms are the Saturn, Playstation, Nintendo 64, Dreamcast, Playstation 2, Xbox, and Gamecube. The sales figures account for approximately 65 percent of the retail stores that sell video games. Due to the fact that some platforms such as the Playstation had over 1,000 games, the top 200 hundred selling games of each platform were selected as the sample size. With each observation being game $s$ for platform $p$ at time $t$, there were 28,733 observations in total. In determining whether the a game was a licensed game or a sequel, Mobygames.com and Videogames.com were used as the primary sources.

6. Data Analysis

6.1 Descriptive Statistics

The descriptive statistics of the 14 variables from equation 1 are presented in the table below:
As shown in the table, the mean of the natural log of game sales was 10.6. When the natural log is converted to standard dollar units, the mean is shown to be 38,948. The min and max of game sales in standard dollar units are 3.42 and 80,197,267.41, revealing that game sales varied greatly during this time.

Below the natural log of game sales, the table reports that the mean for the fourth quarter variable was 27.6 percent. Since this figure is not so much higher than the 25 percent we would expect if the number of game entries was uniform throughout the year, the number indicates a small increase in games available for consumption during the holiday season. However, sales of games during the fourth quarter are a different matter, and it will be explored with the regression results.

Besides the statistics on game sales and the fourth quarter variables, the numbers for platform life and game life are interesting in that game life is almost exactly half of that of platform life at 19.8 versus 38.9. The relatively high standard deviation of 14.7 for game life suggests that the release of games is dispersed greatly during the platform’s
cycle. Taken together, the statistics for platform and game life depict a picture of uniform game release during a platform’s product cycle.

The statistic of considerable interest, however, is the mean of the proportion of entries for information shortcut games. The mean is stated as 64 percent, which can be loosely translated that 64 percent of the games that were in the market from 1995 to 2002 were either sports license, movie license, or sequel games. When broken down to these three types of games, the numbers are 26.8 percent for sports license, 11.7 percent for movie and other licenses, and 25.1 percent for sequel games.

This mean of the proportion of entries for information shortcut games can be interpreted as a supply side statistic that shows how many games of each type the software firms are releasing. The fact that the majority of the games released are information shortcut games hints that software firms are supplying more of such games to meet their greater demand. The magnitude of this greater demand will be shown in a later section, and the changes in supply of the software firms will be examined after the demand analysis.

6.2 Regression Analysis

To begin regression analysis, we start off with a condensed version of regression equation 1 that was presented in section 5.3:

\[ \ln \text{sales}_s,p,t = \beta_0 + \beta_1 4th + \beta_2 \text{time} + \beta_3 \ln \text{type} + \beta_4 \ln \text{total} + \beta_5 \ln \text{IB} + \beta_6 \text{IS} + \beta_7 \text{time*IS} + \frac{u}{u} \]  (2)
We apply OLS estimates on this regression equation and for the rest of the regression equations presented in this paper. In doing so, we assume that the Gauss-Markov assumptions hold. The assumption that there is no heteroskedasticity in the results is the one suspect assumption, but the large sample size is assumed to mitigate much of the differences between OLS and the weighted least squares estimates that might be used in the presence of heteroskedasticity. As for concerns of endogenous variables, much of the endogeneity would reside with the variables of ln type and ln total, but as explained in section 5.2, the added variable of lnIB corrects for the endogenous issues associated with these factors.

The results of the regression equation 2 are presented below:

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>4th</td>
<td>0.739</td>
<td>0.033</td>
<td>22.170</td>
</tr>
<tr>
<td>time</td>
<td>-0.031</td>
<td>0.001</td>
<td>-22.030</td>
</tr>
<tr>
<td>ln type</td>
<td>0.246</td>
<td>0.067</td>
<td>3.680</td>
</tr>
<tr>
<td>ln total</td>
<td>-1.130</td>
<td>0.069</td>
<td>-16.360</td>
</tr>
<tr>
<td>ln IB</td>
<td>0.899</td>
<td>0.015</td>
<td>61.580</td>
</tr>
<tr>
<td>IS</td>
<td>0.760</td>
<td>0.092</td>
<td>8.200</td>
</tr>
<tr>
<td>time*IS</td>
<td>-0.012</td>
<td>0.002</td>
<td>-6.470</td>
</tr>
</tbody>
</table>

R-squared = .149 Coefficients are all significant at a .01 level

The R-squared value is .149, and all the explanatory variables are shown to be significant at the 1 percent level. When looking at the variables individually, we see that for the 4th variable the coefficient is .739. Since sales of games in the fourth quarter are 70 percent higher than that of the rest of the year, the number shows that despite the
constancy of the number of games available throughout the year, the demand of the games are much greater during the holiday season.

For the variable time, the negative figure of -.03 reveals that the sales of game s are declining by 3 percent with each passing month. Since time serves as a proxy for i, the estimate states that the increase in game demand composed of casual gamers is diminishing as the demand becomes greater. Whether there are differences of this effect between information-shortcut and non-information shortcut games will be shown later with the interaction term of time*IS.

After the variable of time, the rest of the picture presented by the results becomes difficult to justify. The coefficients for ln total and ln IB are negative and positive respectively as expected, but the positive coefficient for ln type is read as: A 1 percent increase in the similar number of games increases sales of game s by .24 percent, and it seems illogical that greater competition would increase the sales of game s. Likewise the coefficient for the interaction term time*IS is shown to be negative, which is the opposite of what the model theorizes.

This regression equation 2 is shown to be a poor fit to the model, and it is expected considering that the variables of gen, plat, and game that were discussed previously were not inserted into the equation. We now run regression equation 1 with those added variables to come up with the following results:
OLS Estimates for Regression Equation 1

<table>
<thead>
<tr>
<th>Variable</th>
<th>N=28,733</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>4th</td>
<td>0.695***</td>
<td>0.021</td>
<td>32.7</td>
<td></td>
</tr>
<tr>
<td>time</td>
<td>-0.029***</td>
<td>0.001</td>
<td>-32.44</td>
<td></td>
</tr>
<tr>
<td>gen</td>
<td>-0.225***</td>
<td>0.028</td>
<td>-8.01</td>
<td></td>
</tr>
<tr>
<td>plat</td>
<td>-0.0457***</td>
<td>0.002</td>
<td>-29.74</td>
<td></td>
</tr>
<tr>
<td>game</td>
<td>-0.092***</td>
<td>0.002</td>
<td>-57.9</td>
<td></td>
</tr>
<tr>
<td>ln type</td>
<td>-0.349***</td>
<td>0.053</td>
<td>-6.58</td>
<td></td>
</tr>
<tr>
<td>ln total</td>
<td>-0.163***</td>
<td>0.054</td>
<td>-3.03</td>
<td></td>
</tr>
<tr>
<td>ln IB</td>
<td>1.49***</td>
<td>0.011</td>
<td>133.19</td>
<td></td>
</tr>
<tr>
<td>IS</td>
<td>-0.142</td>
<td>0.091</td>
<td>-1.55</td>
<td></td>
</tr>
<tr>
<td>time*IS</td>
<td>0.008***</td>
<td>0.001</td>
<td>7.03</td>
<td></td>
</tr>
<tr>
<td>gen*IS</td>
<td>0.068*</td>
<td>0.038</td>
<td>1.81</td>
<td></td>
</tr>
<tr>
<td>plat*IS</td>
<td>0.01***</td>
<td>0.0018</td>
<td>5.38</td>
<td></td>
</tr>
<tr>
<td>game*IS</td>
<td>-0.025***</td>
<td>0.002</td>
<td>-12.83</td>
<td></td>
</tr>
</tbody>
</table>

R-squared = .661

*** refers to significance at a .01 level
** refers to significance at a .05 level
* refers to significance at a .10 level

The R-squared value is higher compared to the previous regression results at .661, and this is expected since three more control variables of generation, platform, and game time are added to the regression equation. The coefficients for 4th and time are similar to results from the previous regression in that they are .69 and -.030 respectively in comparison to the .74 and -.030 of the previous results. Below the time variable are the control variables of gen, plat, and game, and the negative coefficients for all three variables fit the proposed economic model that casual gamers enter later in the market for the time dimensions of generation, platform, and game time.

The next set of the three control variables of ln type, ln total, and ln IB, are presented once more, but in this regression equation, the coefficients fit the theoretical model. The coefficient for ln type and ln total are both negative to indicate that more games in the market lessen the demand of games, but the number for ln type is about
twice as large as that of \( \ln \text{total} \) in absolute value at \(-.35\) to \(-.16\) as expected—we would think that a 1 percent increase in the number of similar type of games as game \( s \) would lower its demand more so than a 1 percent increase in the total number of games. In observing these two variables, however, it must be kept in mind that a 1 percent increase in \( \ln \text{type} \) simultaneously increases \( \ln \text{total} \), albeit to a lesser percentage. In order to see the overall reduction in demand of game \( s \) from a 1 percent increase in \( \ln \text{type} \), a weighted calculation must be carried out. Since the mean of the strictly positive numbers of \( \ln \text{type} \) and \( \ln \text{total} \) is shown to be 70 and 130 games (\( e^{4.25} \) and \( e^{4.87} \) respectively, from table 1), a 1 percent increase in \( \ln \text{type} \) is equal to a .54 percent increase in \( \ln \text{total} \) (\( 70/130 = .54 \)). We then multiply .54 percent to \( \ln \text{total} \)'s coefficient of \(-.16\) to get \(-.086\), and we add -.086 to \( \ln \text{type} \)'s coefficient of \(-.348\) to find \(-.44\) as the final answer; a 1 percent increase in the number of same type of game decreases sales of game \( s \) by .44 percent.

For the variable \( \ln \text{IB} \), the coefficient is positive and greater than 1 at 1.49, and this can be interpreted that network effects are present in the video game market as argued by Clements and Ohasi. To explain this network effects more specifically, it seems that as the number of users for a platform increases, the gaming community’s sharing of information through word-of-mouth and chat forums increases the quality of games being produced, which in turn increases the demand for games at a hardware to software ratio that is greater than 1 to 1. Not only are network effects present, they are quite noticeable in that a 1 percent increase in the installed base will increase game \( s \) sales by 1.5 percent.
Beyond the control variables, the dummy variable IS is revealed to be negative, but it is insignificant at the 10 percent level. The lack of precision in the estimate makes it difficult to determine if information shortcut games really do sell less holding time fixed at zero, but it is of little matter to the hypothesis question, for the hypothesis is concerned with the growth in demand of information shortcut games relative to non-information shortcut games through time. This question is best answered looking at the interaction term of time*IS, but before turning to that variable, we observe the other control interaction terms of gen*IS, plat*IS, and game*IS. The coefficient for game*IS is -.02, and we explain this by suggesting that casual gamers tend to buy their games later than hardcore gamers. This habit of buying later for information shortcut games means that their sales fall behind that of non-information shortcut games, and this gap is never closed during game’s life cycle. As for the positive coefficients on gen*IS and plat*IS, since the casual gamers latch on later in both the generation and platform cycles, this increased proportion in later stages of generation and platform time will increase the demand of information shortcut games relative to other games.

We finally turn to the experimental variable of time*IS, for which the coefficient is positive at .008, and significant at the 1 percent level. When this coefficient of .008 is multiplied by 12, we find that sales of information shortcut games grows at a yearly rate that is 9.6 percent higher than that of non-information shortcut games. This rate of 9.6 percent seems to confirm that not only did the increase in the proportion of casual gamers increase the demand of information shortcut games relative to non-information shortcut games, but the increase is also fast in that the sales of these games grew at a rate that was 9.6 percent higher.
This figure of 9.6 percent seems fast, but assuming that it represents the growth of the demand for games comprised of casual gamers, it should be measured against the growth in demand for games composed of hardcore gamers. To do so, we set up the following equation:

\[
\frac{HCg \times x + Cg \times (x + 0.96)}{HCg + Cg} = VGg
\]

where \( HCg \) is the yearly growth of hardcore gamer base from 1995 to 2002, \( x \) is the yearly hardcore gamer demand growth, \( Cg \) is the yearly growth of casual gamer base from the same period, \( (x + 0.96) \) is the yearly casual gamer growth, and \( VCg \) is the yearly growth of the video game market.

The numbers obtained for these variables are rough estimates, but for \( HCg \), the U.S. census reports that the population of males of ages 13-25 (the group most likely to be hardcore gamers) grew from 24,193,307 in May 1995 to 26,830,60 by February 2002—an increase of about 11 percent, or a yearly increase of .016. For \( Cg \), we rely on both Brenda Laurel and ESA’s combined information that the proportion of girl gamers was about 25 percent around 1995 and 39 percent by 2004. When the growth is divided yearly, it comes out to a rate of 0.081. Finally, for \( VCg \) we use the IDSA report that the video game industry grew at a rate of 15 percent per year from 1997 to 2000. These numbers are inserted into the equation to solve for \( x \), the hard core demand growth per year:

\[
\frac{.016x + .081(x + .096)}{.097} = .15
\]

Solving the equation we find that \( x \) equals .0695, and so the hardcore gamer demand growth per year was 6.95 percent during 1995 to 2002. The casual gamer
demand growth per year was $6.95 + 9.6 = 16.55$ percent, and therefore the casual gamer
growth was 138 percent higher than that of hardcore game growth in this time period.

The results from regression equation 1 seem to answer the hypothesis question,
and the next step is to divide the information shortcut variable into the three categories of
sports license, film and other license, and sequel variables. The regression equation is
lengthened into the following:

$$
\ln \text{sales}_{s,t} = \beta_0 + \beta_{14}\text{time} + \beta_{12}\text{gen} + \beta_{11}\text{plat} + \beta_{13}\text{game} + \beta_{10}\ln \text{type} + \beta_{17}\ln \text{total} + \\
\beta_{12}\ln IB + \beta_{16}\text{film} + \beta_{15}\text{sequel} + \beta_{13}\text{time}^*\text{film} + \beta_{14}\text{time}^*\text{sequel} + \\
\beta_{15}\text{gen}^*\text{sports} + \beta_{16}\text{gen}^*\text{film} + \beta_{17}\text{gen}^*\text{sequel} + \beta_{18}\text{plat}^*\text{sports} + \beta_{19}\text{plat}^*\text{film} + \\
\beta_{20}\text{plat}^*\text{sequel} + \beta_{21}\text{game}^*\text{sports} + \beta_{22}\text{game}^*\text{film} + \beta_{23}\text{game}^*\text{sequel} + u
$$

In this equation, the \textit{sports} variable includes licenses of professional sports
leagues, endorsements from individual athletes such as pro skater Tony Hawk, and some
of the more extreme “sports leagues” such as the World Wrestling Federation and the
racing car circuit NASCAR. For the variable \textit{film}, the vast majority of the games were
film tie-in games, but some of the other license games were TV shows, board games, and
toys such as Barbie. In the \textit{sequel} dummy variable, the obvious sequel games were direct
follow-ups such as Metal Gear Solid 2, but it also counted games that included
recognizable characters from previous games such as \textit{Mario Party}. This variable,
however, did not count games that were also had sports or other licenses in order to avoid
double counting. The coefficients of $\beta_{12}$-$\beta_{23}$ present the interaction terms of the different
types of games with the four time dimensions. The regression estimates are shown in the
following:
### OLS Estimates for Regression Equation 3

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>4th</td>
<td>0.686***</td>
<td>0.021</td>
<td>32.99</td>
</tr>
<tr>
<td>time</td>
<td>-0.025***</td>
<td>0.001</td>
<td>-29.12</td>
</tr>
<tr>
<td>gen</td>
<td>-0.193***</td>
<td>0.027</td>
<td>-7.03</td>
</tr>
<tr>
<td>plat</td>
<td>-0.0377***</td>
<td>0.001</td>
<td>-25.99</td>
</tr>
<tr>
<td>game</td>
<td>-0.095***</td>
<td>0.002</td>
<td>-60.71</td>
</tr>
<tr>
<td>ln type</td>
<td>0.208***</td>
<td>0.038</td>
<td>5.42</td>
</tr>
<tr>
<td>ln total</td>
<td>-0.741***</td>
<td>0.039</td>
<td>-18.76</td>
</tr>
<tr>
<td>ln IB</td>
<td>1.45***</td>
<td>0.011</td>
<td>131.18</td>
</tr>
<tr>
<td>sports</td>
<td>0.99***</td>
<td>0.122</td>
<td>8.11</td>
</tr>
<tr>
<td>film</td>
<td>0.418**</td>
<td>0.192</td>
<td>2.17</td>
</tr>
<tr>
<td>sequel</td>
<td>0.074</td>
<td>0.115</td>
<td>0.64</td>
</tr>
<tr>
<td>time*sports</td>
<td>0.004***</td>
<td>0.001</td>
<td>2.72</td>
</tr>
<tr>
<td>time*film</td>
<td>-0.006***</td>
<td>0.002</td>
<td>-2.88</td>
</tr>
<tr>
<td>time*sequel</td>
<td>0.004***</td>
<td>0.001</td>
<td>3.11</td>
</tr>
<tr>
<td>gen*sports</td>
<td>-0.082*</td>
<td>0.048</td>
<td>-1.72</td>
</tr>
<tr>
<td>gen*film</td>
<td>0.161**</td>
<td>0.067</td>
<td>2.39</td>
</tr>
<tr>
<td>gen*sequel</td>
<td>-0.062</td>
<td>0.045</td>
<td>-1.38</td>
</tr>
<tr>
<td>plat*sports</td>
<td>-0.009***</td>
<td>0.002</td>
<td>-4.5</td>
</tr>
<tr>
<td>plat*film</td>
<td>0.011***</td>
<td>0.002</td>
<td>4.43</td>
</tr>
<tr>
<td>plat*sequel</td>
<td>0.009***</td>
<td>0.002</td>
<td>4.52</td>
</tr>
<tr>
<td>game*sports</td>
<td>-0.037***</td>
<td>0.002</td>
<td>-16.42</td>
</tr>
<tr>
<td>game*film</td>
<td>-0.019***</td>
<td>0.003</td>
<td>-6.59</td>
</tr>
<tr>
<td>game*sequel</td>
<td>-0.005***</td>
<td>0.002</td>
<td>-2.17</td>
</tr>
</tbody>
</table>

R-squared = .6750

*** refers to significance at a .01 level
**  refers to significance at a .05 level
*   refers to significance at a .10 level

Observing the control variables that were present in the previous regression equations, the variable ln type stands out in that the coefficient is positive and does not fit the theoretical model when it did in regression equation 1. As for the three dummy variables of sports, film, and sequels, the coefficients are all positive. However, only sports is significant at the 1 percent level, and the dummy variables provide no answer to the hypothesis question. Looking at the control interaction terms, we see that game*sports, game*film, and game*sequel are all negative as expected, but the interaction terms at the platform and generation level are less consistent. The platform
interaction terms are all significant at the 1 percent level, but platform*sports is negative, which strays from our expectation.

We now turn to the experimental variables of time*sports, time*film, time*sequel, and they are all shown to be significant at the 1 percent level. Yet, the estimates are problematic in that the time*film coefficient is negative at -.0058. This is particularly surprising in that our discussion of the three information shortcut type of games, games with film license tie-ins were guessed to have the largest increase in sales with the increase in proportion of casual gamers in the market. A possible conjecture for this negative coefficient is that these film license-games receive less favorable reviews than that of non-film games. As Internet usage has grown over the years, gamers, especially hardcore gamers, have become more knowledgeable of these reviews and have increasingly stayed away from these film-based games.

The negative estimate for time*film and its resultant speculation reveals that as a collective whole it is clear the demand for information shortcut games have increased relatively faster than that of non-information shortcut games, but it is difficult to give concrete explanations when such games are subdivided into the three categories. Much of this has to do with the “noise” of the hardcore demand for these information shortcut games as discussed in section 4.2. That section predicted as to how the hardcore demand would affect the three variables of sports, film, and sequel in capturing the demand for information shortcut games, but the regression results do not match the theory that film-license games would see the greatest increases in demand followed by sequels then sports license games. Therefore, a detailed investigation of the information shortcut variable in its various subsets is left to further study.
6.3 The Supply Side of Information Shortcut Games

As shown by the results from regression equation 1, casual gamer demand has grown at a yearly rate that was 138 percent faster than that of yearly growth of hardcore gamer demand, and with such a trend, we should expect the software firms to release more information shortcut games over the years to meet that demand. As stated in the descriptive statistics section of the paper (6.1), the proportion of entries that were information shortcut games was .637. This proportion serves as a proxy that 63.7 percent of the games available were such type of games. But the more interesting aspect of this number is to break it down by type of information shortcut game and by year to better observe the phenomenon. The table for such data is presented below:

Percent of Entries that are Information Shortcut Games (May 1995-February 2002)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>sport</td>
<td>22.9</td>
<td>13.1</td>
<td>21.2</td>
<td>26.2</td>
<td>31.0</td>
<td>29.4</td>
<td>26.3</td>
<td>27.4</td>
</tr>
<tr>
<td>movie</td>
<td>2.9</td>
<td>4.0</td>
<td>8.8</td>
<td>9.6</td>
<td>10.7</td>
<td>13.2</td>
<td>14.2</td>
<td>13.7</td>
</tr>
<tr>
<td>sequel</td>
<td>12.4</td>
<td>20.4</td>
<td>23.6</td>
<td>23.5</td>
<td>26.8</td>
<td>27.0</td>
<td>26.5</td>
<td></td>
</tr>
<tr>
<td>total</td>
<td>38.2</td>
<td>37.5</td>
<td>53.1</td>
<td>59.4</td>
<td>65.2</td>
<td>69.4</td>
<td>67.5</td>
<td>67.6</td>
</tr>
</tbody>
</table>

As seen in the table, the percent of information shortcut games available increased from 38.2 percent in 1995 to 67.6 percent by February of 2002—an increase of 77 percent. All three variables of sports, movie, and sequel show increases during the time period, but the sports variable seemed to have reached a peak in 1999 before dipping a bit in the following years whereas the release of movie and sequel games displayed a steady
climb over the years. A graph of the table is presented below to better illustrate the situation:

![Information shortcut game sales entries/overall game sales entries graph](image)

The analysis above hint that software firms were aware of the rising demand for information-shortcut games and increased their supply of such games. The plateau at the tail end of most of the series on the graph could be displaying two effects occurring at the same time: First, it could be that $\delta$ had started to plateau sometime around 2000, and the growth in supply of games in turn leveled off. Second, the tail end of the graph covers the period when the 32-bit generation platforms were ending their runs while the 128-bit generation platforms were just being introduced the market. Since casual gamers are thought to be late entrants of a video game generation, the plateau could signify a
temporary stagnation in the supply of information-shortcut games until more casual
gamers enter the market.

It is possible, however, to separate out this late casual gamer entry effect within a
video game generation and still observe the effect of casual game demand on game
supply. The following table presents the number of months it took for the number of
information shortcut games to surpass the number of non-information shortcut games for
each platform in the sample:

<table>
<thead>
<tr>
<th>Platform</th>
<th>Release Date</th>
<th>Months before overtaking</th>
<th>Platform</th>
<th>Release Date</th>
<th>Months Before overtaking</th>
</tr>
</thead>
<tbody>
<tr>
<td>Saturn</td>
<td>May 1995</td>
<td>27</td>
<td>Dreamcast</td>
<td>Sept 1999</td>
<td>11</td>
</tr>
<tr>
<td>PS1</td>
<td>Sept 1995</td>
<td>15</td>
<td>PS2</td>
<td>Oct 2000</td>
<td>5</td>
</tr>
<tr>
<td>N64</td>
<td>Sept 1996</td>
<td>0</td>
<td>Xbox</td>
<td>Nov 2002</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Gamecube</td>
<td>Nov 2002</td>
<td>0</td>
</tr>
</tbody>
</table>

As seen in the columns for the 32-bit generation, the Nintendo 64
immediately had more information shortcut games than not upon its release, while for the
Sega Saturn it took over two years before the overtaking occurred. It should be noted
that Saturn was also released the earliest of the three 32-bit systems on May 1995 while
the N64 was released the latest on September 1996. The fact that it took the latest
platform much less time to have more information-shortcut games than non-information
shortcut games suggests that as time progressed, software firms were releasing more
information shortcut games in new platforms compared to non-information shortcut
games.
When we look at the 128-bit generation that arrived after the 32-bit generation, we again can see the trend that platforms released later took less longer in providing more information shortcut games than non-information shortcut games. Not only did the trend continue, the time needed for the platforms for this overtaking to occur was also less in that the platform that was released first, the Dreamcast, needed 11 months versus 27 for the Saturn, and the platform that was released second, the Playstation 2, needed only 5 months compared to 15 for the original Playstation. Such a pattern supports the notion that as the video game industry aged, the software firms were releasing more information shortcut games, and they were releasing them sooner during a platform’s product cycle.

7. Conclusion

The results of the regression estimates show that in the broad course of video game history, the increase in proportion of casual gamers in the industry has increased the demand of games that provide information shortcuts. As evidenced by the positive and substantial coefficient of the interaction term $time*IS$ for regression equation 1, casual gamer demand grew at a rate 9.6 percent higher than that of hardcore gamer demand. A rough estimate of the yearly growth in hardcore demand was calculated as 6.95 percent, and thus casual gamer demand’s yearly growth was shown to be a rapid 16.55 percent over the 7 year stretch from 1995 to 2002.

This study argued that casual gaming had increased based on anecdotes and reports that the proportion of older and female gamers had increased over time. As a matter of further study, the measurement of casual gaming might be changed to
something such as the number of average hours played by a gamer, and these other variables will give better insight as to whether casual gaming really has increased in the video game industry through time. Another study that could be conducted later in the future would be to simply extend the time line from February 2002 to the current period of May 2005; much of the hoopla surrounding the sudden popularity of information shortcut games was reported in the last year or so, and therefore, a study that encompasses the sales of the latest games may reveal a more dramatic impact of mainstreaming in the video game industry.

At the start of this paper, it was understood that the proportion of casual gamers had increased in the video game market, and the question then was how this increased had impacted the demand of the games. There were two general ways that this mainstreaming of the industry might have affected the composition of the games. The first approach would have been to expand the product variety of games to cater to the tastes of new sub-groups of casual gamers. The content of the games would have evolved from the standard search-and-destroy missions to other forms of game experiences such as slower-paced narrative games for older casual gamers or “girl games” for female casual gamers that focus on objectives such as cooperating with friends and building objects rather than destroying them.* The second response in the trajectory towards the mainstream audience would have been to focus on the marketing end of the game. The use of licenses and cultivation of brand names would attract the casual gamer who was less willing to spend the necessary time to gather the information of a game’s content. The results from this paper show that the demand for the latter kind

* In an interview, Brenda Laurel states that psychological research conducted by her and her colleagues show that females were thought to have intrinsically different game-playing patterns of one of which was a preference for cooperation in contrast to competition for males.
of game went up with the mainstreaming of the industry, and the software firms met this increased demand by supplying more information shortcut games.

While the paper did not run an alternate test to see the impact on the demand for games tailored to the casual content, anecdotal evidence suggests that such games were not as successful in attracting the eye of the casual gamer. An infamous example is the failure of the girl games company Purple Moon Company. Started by game designer Brenda Laurel, the company’s objective was to provide games for what was perceived as a largely untapped female gamer market. Despite extensive market research and release of innovative games for girls, the company faced financial troubles by 1998 and was eventually bought up by the rival company Mattell (Kline, Witheford, Peuter 2003). In speaking of the uncertainty in trying to design games for this new group of female gamers, game designer John Romero shrugs, “Men design games for themselves because they understand what they know is fun. They don’t understand what women find fun.”

In a slight variation of this quote, it seems from the lack of casual-tailored games, hardcore game designers do not understand what casual gamers find fun. When this greater uncertainty in producing casual-specific games is coupled with the rising supply costs of games due to larger production teams, software firms were merely displaying rational economic behavior in providing information shortcut games rather than expanding product variety.

This growing trend towards information shortcut games depicts an undesirable scenario for hardcore gamers who might disregard such games as ones that lack innovation and creativity; the majority of the budget and time of information shortcut games may be spent on acquiring licenses, or in the case of a sequel, the presence of a
predecessor allows for formulaic design of the game. There are signs that such a scenario is already coming into fruition, as game developer American McGee declares, “The game industry is not interested in original ideas. We don’t even waste our time pitching them (Taub 2004).” But before the demise of the innovative game can be fully announced, it must be kept in mind that video game history has been littered with surprising twists and turns through its short course. When Nintendo was catering its NES platform to the adolescent boy during the late ’80s, it would have been difficult to imagine that a decade later the average age of gamer would be 29, and that there would be a 39 percent chance that the gamer would be female. Likewise, even as the course of industry heads towards a casual direction, it would seem premature to declare that the end of innovative software has arrived in the home video game industry.
8. Bibliography


Laurel, Brenda. Phone Interview. 16 January 2005.


9. Appendix

Many different regression equations that were experimented with did not make it into this paper. A sample of these other regression estimates are put on display in the appendix without further interpretation of these results.

Table 1

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R-squared = .1006
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** refers to significance at a .05 level
* refers to significance at a .10 level
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** refers to significance at a .05 level  
* refers to significance at a .10 level

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*** refers to significance at a .01 level  
** refers to significance at a .05 level  
* refers to significance at a .10 level
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R-squared = .0296
All coefficients are significant at a .01 level

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R-squared = .0480
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** refers to significance at a .05 level

### Table 6

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R-squared = .786
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** refers to significance at a .05 level
* refers to significance at a .10 level
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R-squared = .4786

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* refers to significance at a .10 level