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Product Quality and Technological Change - Evidence from the Computer Games Industry

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Abstract

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Traditional vertical differentiation literature argues that firms differentiate their products in order to avoid price competition. In such theoretical models, the firm producing the highest quality good also enjoys the largest market share. However, would this still hold if demand is non-linear in product quality?

We argue for the existence of several cases in which higher quality prohibits individuals from consuming the product. This is true for industries which, in order to use the primary product, require a complementary good, that additionally needs to satisfy certain requirements (like in the computer games industry). Here, we assume that requirements for the complementary good increase with the quality of the primary product. Therefore, all potential consumers, whose complementary good is not powerful enough, will not be able to use the product and hence refrain from buying. Firms then have to trade-off product attractiveness with market potential when choosing quality for new products. Because of this, we expect to find an inverted-U-shaped relationship for quality and demand for these industries.

Further, once a product is introduced to the market, its characteristics cannot be changed; i.e. the absolute quality remains flat for the rest of the product life cycle. Technological change has then two implications: On the one hand, innovations lead to higher quality substitutes for the product but on the other hand also increase average quality of complementary goods. While the first effect decreases attractiveness, the latter increases market potential.

To test our theory, we use the computer games industry as the empirical context of our study. This one is well-suited for the analysis as gamers need to have a complementary good, the PC, which additionally has to fulfill minimum system requirements. We use game-specific information such as release date, genre and system requirements from MobyGames and GameSpot. Revenue Data is drawn from the NPD Group and Futuremark provides 1.5 million benchmark results between 2001 and 2010 which we use as an indicator of hardware availability and technological change of the complementary products.

The results suggest that a game's total revenue increases in technological quality; however, we find a decreasing marginal effect of technological quality. Moreover our findings reveal that faster technological pace is detrimental to the success of a game as better substitutes become available and consumers prefer buying newer products. However, the effect of technological pace turns positive if the product's initial technological quality was sufficiently high. In this case, technological pace increases market potential as average hardware availability improves and more consumers are able to play the game.

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Product Quality and Technological Change – Evidence from the Computer Games Industry

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Abstract

We argue for the existence of several cases in which higher quality prohibits individuals from consuming the product, thus limiting demand. This is true for industries like the computer games industry which, in order to use the primary product, require a complementary good that additionally needs to satisfy certain requirements. Assuming that requirements for the complementary good are positively correlated with primary product quality, firms have to trade-off product attractiveness with market potential. Because of this, we expect to find an inverted-U-shaped relationship for quality and demand for these industries.

Further, once a product is introduced to the market, its characteristics cannot be changed; i.e. the absolute quality remains flat for the rest of the product life cycle. Technological change has then two implications: On the one hand, innovations lead to higher quality substitutes for the product but on the other hand also increase average quality of complementary goods. While the first effect decreases attractiveness, the latter increases market potential.

To test our theory, we use the computer games industry as the empirical context of our study. Using a panel of 506 games between 2001 and 2008, the results suggest that a game's total revenue increases in technological quality; although at a decreasing marginal rate. Moreover our findings reveal that faster technological change is detrimental to the success of a game as better substitutes become available. However, the effect of technological change turns positive if the product's technological quality is sufficiently high. In this case, technological change increases market potential as average hardware availability improves and more consumers are able to play the game.

Keywords: Vertical Differentiation, Technological Change, Computer Games Industry

JEL Classification: tbd

1. Introduction

Traditional vertical differentiation literature argues that firms differentiate their products vertically in order to avoid price competition. Consumers, differing in their preferences for quality, will then buy the product that maximizes their utility. In this particular model, the firm producing the highest quality good also enjoys the largest market share. However, what would happen if high quality would be detrimental to product success (even if it would come at zero production costs)?

We argue for the existence of several cases in which higher quality prohibits individuals from consuming the product, even though they would have the sufficient willingness to pay. This is true for industries which require a complementary good in order to use the primary product; some of them even making particular demands on the nature of the complementary good. This means that, for utilizing the primary good, the consumer needs not only to possess the complementary good but also it is required to satisfy certain criteria.

While higher quality diminishes market potential it increases product attractiveness at the same time. In order to clarify this point, the computer game industry serves as a good example. Here, the perceived quality of a game is highly correlated with the lavishness of graphical effects which in turn result in higher system requirements. In order to receive a positive utility[1] from the primary good - the computer game - a potential consumer is required to have a secondary good of sufficient quality, i.e. a computer with an appropriate hardware configuration. Individuals who do not own a computer meeting the requirements are therefore excluded from the consumption of the good. We therefore expect quality and demand to have an inverted U-shaped relationship.

Further, once a product is introduced to the market, its characteristics cannot be changed; i.e. the absolute quality remains flat for the rest of the product life cycle. Technological change has then two implications: On the one hand, innovations lead to higher quality substitutes for the product but on the other hand also increase average quality of complementary goods. While the first effect decreases attractiveness, the latter increases market potential.

This raises two specific questions that we address in this paper:

- Is there an inverted U-shaped relationship for product quality and demand?
- How are sales moderated by technological change?

[1] It seems reasonable to assume that a gamer would not get any benefit from just possessing the game and not actually being able to play it.

The empirical context of our study is the computer game industry, which is well-suited for the analysis as system requirements exclude certain individuals from the consumption. We draw our data from four different sources. First, we use a dataset from Futuremark, with roughly 1.5 million benchmark results between 2002 and 2010. Using this data, we can calculate a measure for monthly hardware availability on the market and the panel structure of the dataset indicates the pace of technological change. In addition, the NPD group provides a panel with monthly revenue and sales data for the computer games, and we use MobyGames as a source for game-specific information like genre and release date. Additionally, GameSpot provides system requirements for the games which are then matched with the benchmark scores from the Futuremark dataset to obtain a measure of relative technological quality.

Our first major result is that games with higher technological quality are more successful. While higher system requirements reduce market potential, the better game quality increases the likelihood of consumers buying the game. However, our results show a decreasing marginal effect suggesting an inverted U-shaped relationship for demand and quality. Second, our findings indicate that the effect of technological quality is negative which captures the effect of competition through better substitutes. Third, the effect of technological change turns positive if technological quality is sufficiently high. In this case, the market potential increasing effect outweighs the negative effect of substitutes.

Our paper is (to our knowledge) the first to investigate empirically exclusion of consumers as a result of increasing product quality. Recent literature on vertical product differentiation assumes individual preferences to be distributed uniformly across population, leaving the profit maximizing firms with a decision on product quality and prices (Gabszewicz and Thisse, 1979; Shaked and Sutton, 1982; Moorthy, 1988; Tirole, 1988). In a regular duopoly, firms choose distinct qualities, thus relaxing price competition. Our paper contributes to this literature by investigating vertical differentiation in industries where demand is nonlinear in quality. While in standard models of vertical differentiation the first mover chooses the highest quality and consequently earns the highest market share, our model suggests the existence of an optimal point of quality. Additionally, we explore the effect of advancing technology on the choice of quality.

Our paper is structured as follows: In section 2, we give an overview of present literature. Section 3 presents our model and section 4 briefly outlines the computer game industry. Section 5 introduces the data and variables used in our regression while section 6 presents the empirical specification as well as the results which are then discussed in section 7. Section 8 concludes.

2. Related Literature

It is commonly recognized that firms employ a variety of strategies to differentiate their good from other firms' products in order to soften competition. Product differentiation exists when, within a group of goods that can be considered to form a product class, there is a variety of similar but not identical goods. The theory of product differentiation has been associated with the theory of monopolistic competition (Lancaster, 1975) because firms producing heterogeneous outputs will face a downward-sloping demand curve[2] (Hart, 1979).

The special case of firms differentiating their products through quality is known as vertical product differentiation[3]. Several scholars explored conditions in which firms choose the qualities of their products first and prices afterwards (Wang & Yang, 2001; Moorthy, 1988. Moreover, these models differ with regard to the distribution of consumer types. In some cases consumers are heterogeneous with regard to tastes (Wauthy, 1996; Hauser, 1988; Hauser & Wernerfelt, 1988), in others regarding income (Gabszewicz & Thisse, 1979; Shaked & Sutton, 1982). While some models restrict their analysis to a duopoly (Tirole, 1988; Choi & Shin, 1992), others allow for multiple firms to participate in, or enter the market (Shaked & Sutton, 1982).

The model of Tirole (1988) proposes a model in which a monopolist produces a good of a certain quality *v* and sells it at a price *p*. Consumers have preferences for quality $\theta$and buy either one or zero units of the product. The utility then reads

$$U = \begin{cases} \theta v - p & if\ he\ buys\ the\ product \\ 0 & if\ he\ does\ not\ buy \end{cases}$$

Tirole assumes that all consumers prefer high quality for a given price. Obviously a consumer with strong preferences for quality will be willing to pay more for a given quality.

A consumer will then buy the product if $\theta v - p > 0$ and hence $\theta > p/v$. Demand is eventually given by

$$D = N[1 - F(p/v)]$$

[2]As opposed to the case of perfect competition in which individual firms are too insignificant, relative to the market, to influence the market price. Hence, each firm faces a horizontal demand curve and sets price equal to marginal costs (Hart, 1979).

[3] The complementary theory of horizontal product differentiation, or spatial competition, was pioneered by Hotelling (1929) and his ``Principle of Minimum Differentiation''.

where N denotes the total number of consumers. Demand increases in product quality and decreases in price; however, the relationship is linear for both variables.

3. Modelling

Our model investigates a monopolistic firm that offers a product to its potential consumers at a certain quality v and a price p. Assuming a monopoly, we can focus on the strategic choice of quality setting without having to consider any competitive pressure. We further assume that consumers are identical in their incomes but differ with regard to their secondary good quality θ_i, which is uniformly distributed over the interval $[0,\varphi]$ with a density μ[4]. Secondary good qualities are exogenously assigned to consumers which then either buy the product or choose the outside option which yields an utility of zero at no cost.

3.1. A one-period model

Our approach follows the above mentioned notation of Tirole (1988). We assume that the utility function takes the form

$$U_i = \begin{cases} 0 & if\ \theta_i \leq v \\ \sqrt{\theta_i - v} + v - p & if\ \ \theta_i > v \end{cases}$$

If a consumer's secondary good's quality is lower than the product's quality she cannot use it and therefore will not buy it. Her utility, therefore, is zero. In the other case, she benefits from better product quality and from an increasing difference between her secondary good's quality and the requirements $\theta_i - v$. The latter factor, however, shows a decreasing marginal rate.

Equating the utility function of a potential user with the net utility from not buying, zero, we derive the indifferent consumer $\bar{\theta}$, who will differentiate the range of potential consumers into one group preferring the good and one group choosing not to buy. Solving for θ we get

$$\bar{\theta} = (p - v)^2 + v \tag{1}$$

One has to consider that it may not be profitable for all consumers whose $\theta_i > v$ because the price of the product reduces the net utility of the good below the net utility of the outside option.

Assuming zero costs, the profit function of the monopolistic firm is

$$\pi = (\varphi - \bar{\theta}) * p \tag{2}$$

[4] For simplicity, we set, without loss of generality, $\mu = 1$

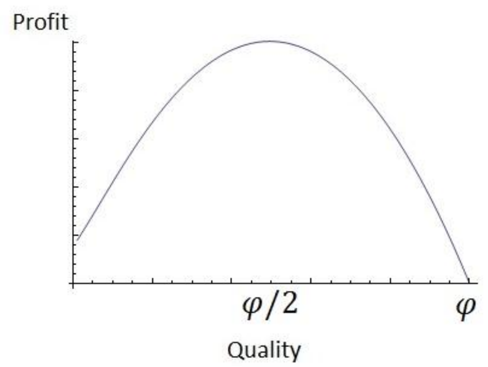
Inserting $\bar{\theta}$ from (1) and differentiating with respect to p, we obtain the following FOC:

$$p(v) = \frac{1}{3}(2v + \sqrt{3\varphi - 3v + v^2}) \tag{3}$$

Before we continue, we insert this derivative into the profit function which now solely depends on v.

$$\pi(v) = \frac{1}{3}(2v + \sqrt{3\varphi - 3v + v^2})(1\varphi - v - (-v + \frac{1}{3}(2v + \sqrt{3\varphi - 3v + v^2}))^2) \tag{4}$$

Plotting the profit against different choices of v, we then get an inverted U-shaped graph:



***PROPOSITION1**:* In industries where requirements on complementary goods exclude certain consumers, profit and quality have an inverted U-shaped relationship.

We then take the first derivative for quality which is given by

$$v(p) = \frac{1}{2}(-1 + 2p) \tag{5}$$

Using (3) and (5) we are then able to compute the equilibria values for quality and price:

$$v *= \frac{1}{8}(-3 + 4\varphi) \tag{6}$$

$$p *= \frac{1}{24}(-6 + 8\varphi + \sqrt{(9 + 4\varphi)^2}) \tag{7}$$

3.2. A multi-period version

We now allow the firm to operate over two periods. While the firm can set prices in each period, it has to set quality before the first period, which will then remain constant over the two periods. However, the secondary good qualities are assumed to advance at a rate of δ which reflects the technological change. The same applies to the net utility of the outside option. Consumers are assumed to buy either the good or the outside option in each period; whichever maximizes their utility. While the utility for the consumers in the first period is the same as in (1), it changes to

$$U_i^{t=2} = \sqrt{\theta_i(1+\delta) - v} + v - p \tag{6}$$

in the second period. Likewise the indifferent consumer becomes

$$\overline{\theta_{t=2}} = \frac{(p-v)^2 + v}{(1+\delta)} \tag{7}$$

Similarly to (2), the profit function follows as

$$\pi = p(-(p-v)^2 - v + \varphi) + p(-\frac{(p-v)^2}{1+\delta} - \frac{v}{1+\delta} + \varphi) \tag{8}$$

and its first order condition is

$$\frac{\partial\pi}{\partial p} = -2p(p-v) - \frac{2p(p-v)}{1+\delta} - (p-v)^2 - \frac{(p-v)^2}{1+\delta} - v - \frac{v}{1+\delta} + 2\varphi \tag{9}$$

$$p(v,\delta,\varphi) = \frac{2(2+\delta)v + \sqrt{(2+\delta)(-3(2+\delta)v + (2+\delta)v^2 + 6(1+\delta)\varphi)}}{3(2+\delta)} \tag{10}$$

The first derivative for quality yields

$$v(p) = \frac{1}{2}(-1+2p) \tag{11}$$

Using (11) and (12) we can then calculate equilibrium value for quality which is given by

$$v^* = \frac{1}{2}\left(-1 + \frac{2+\delta+8\varphi+8\delta\varphi}{4(2+\delta)}\right) \tag{12}$$

(12) indicates that the intertemporarily optimal quality level is higher than in the one period setting. This is due to the positive effect of faster technological change, which can be seen in (13):

$$\frac{\partial v^*}{\partial\delta} = \frac{1}{2}\left(\frac{1+8\varphi}{4(2+\delta)} - \frac{2+\delta+8\varphi+8\delta\varphi}{4(2+\delta)^2}\right) > 0 \tag{13}$$

PROPOSITION2: Faster technological change leads to higher optimal quality.

This result is in line with expectations since the firm needs to consider higher demand in period 2 as the quality of the average quality increases. As more individuals satisfy the requirements, market potential increases.

Using this optimal quality level, the optimal price in follows as

$$p^* = \frac{2+\delta+8\varphi+8\delta\varphi}{8(2+\delta)} \tag{14}$$

Comparing these results to those in the one-period-setting shows that technological change leads to higher prices and quality. Intuitively, the firm needs to compensate for the perceived lower quality of the product. Technological change outdates the good in period 2 which cannot be changed after its introduction. However, the firm can counter this effect by lowering prices.

3.3. Introducing Competition

In the last section, the effect of technological change was purely positive as it simply increased market potential. However, technological change also leads to better substitute products. For this, we account in this extension of our model in which the utility from the product needs to exceed that of the outside option. The utility of the latter is assumed to be non-negative and increases in technological change.

Consumers then buy the product (in the first period) if

$$U(v,p) > \omega$$

$$\bar{\theta} = (\omega+p-v)^2 + v \tag{15}$$

where ω denotes the net utility of the outside option. The marginal effect of the outside option on the profit of the monopolist is negative as the first derivative indicates:

$$\frac{\partial\pi}{\partial\omega} = -\frac{2+\delta-8\omega-4\delta\omega+8\varphi+8\delta\varphi}{8+8\delta} < 0$$

PROPOSITION3*:* The availability of better substitutes has a negative effect on profits.

Equilibrium values for price and quality are then given by

$$v* = -\frac{1}{2}+\omega+\frac{2+\delta-8\omega-4\delta\omega+8\varphi+8\delta\varphi}{8(2+\delta)} \tag{16}$$

and

$$p*=\frac{2+\delta-8\omega-4\delta\omega+8\varphi+8\delta\varphi}{8(2+\delta)} \tag{17}$$

4. Empirical Context

To test our theory, we use the computer games industry as the empirical context of our study. This one is well suited for the analysis, as gamers need to have a complementary good, the PC, which additionally has to fulfill minimum system requirements. Hardware requirements are a fair indicator for game quality as better graphical and physical effects by definition translate into higher requirements. For firms in this environment, we identified two main trade-offs related to setting game quality. First, higher quality diminishes market potential but, on the other hand, increases product attractiveness. Second, developers have to take the effect of technological change into account; the introduction of technologically more sophisticated substitutes will have a negative effect while, on the other hand, the average quality of computers will rise which increase market potential. However, producing high quality is costly so that firms cannot simply produce the highest possible quality and wait until technological change generates sufficient market potential. Both trade-offs are discussed in more detail in the following subsections.

4.1. Excluding potential consumers

Clearly, technological advances gave developers room for powerful graphics and more realistic game physics, which doubtlessly contributed to the advance of computer games. However, developers face a trade-off when setting quality. On the one hand, better graphics contribute to the quality of the game and therefore increase the likelihood of users buying it. On the other hand, the sophistication of graphical effects raises system requirements. This excludes those gamers whose PCs cannot provide sufficient computing power, thus limiting market potential. Hence, the developer has to make a strategic decision of whether he prefers to sell a product of lower quality to a larger market or, vice versa, a high-quality game to a smaller market. The relevant question in this case is whether the sales-enhancing effect of increased product attractiveness through better game quality can exceed the sales-reducing effect of lower market potential.

As Proposition1 suggests, we expect to find an inverted U-shaped relationship for quality and demand. Consider a hypothetical game with maximum system requirements. Although it would be highly appealing because of its graphical effects, the market potential would be reduced to a handful of gamers.

4.2. Technological Change

In 1965, Gordon Moore made a prediction (which today is commonly known as Moore's Law) that transistor density of integrated circuits would double about every two years (Moore, 1965). Time should prove this assumption correct. Figure 1 gives a striking overview of the data provided by the Futuremark dataset, clearly revealing that the computing power increased drastically over a 9-year period.

INSERT FIGURE 1 HERE

During this time span, the average benchmark score (lower graphic) skyrocketed from roughly 2,318 in January 2001 to almost 53,000 in January 2010, which equals an increase by a factor of 22.8.

In line with Proposition 2 and 3, technological change has two implications. First, computer games that were cutting-edge at the date of launch might be surpassed by better substitutes only 12 months later. With absolute game quality remaining constant, relative quality decreases over time because more sophisticated products are introduced. On the other hand, as more powerful PCs are bought, hardware availability improves which increases market potential. Put differently, market potential increases while product attractiveness decreases.

This raises again the question of how to strategically best set technological quality considering this effect. From a naïve point of view, one would assume that firms should choose the highest quality possible. This way the product would not be threatened by better substitutes and technological change would, by definition, increase market potential over time.

However, costs for producing higher quality increase exponentially in quality, which renders producing cutting-edge products uneconomically.

This implies another interesting trade-off for game developers: Either they choose a lower level of game quality, save costs but risk disappearing from the market earlier, or they choose a costly, higher level. In the latter case, the computer game would realize lower sales during the first stage (due to smaller market potential) but report above average figures in the following periods.

5. Data

5.1. Sources of Data

Our empirical analysis combines several sources of data. First, we use a dataset from MobyGames, the world's largest video game documentation project, which provides detailed information regarding genre and release date, and indicates further if a game uses licensed content, is part of a series, or utilizes a third party graphics engine.

This is paired with a dataset from the NPD Group, a leading organization tracking this industry. This NPD data provides monthly unit and dollar sales and covers the period 1995-2008[5], inclusive. The sales numbers are based on a sample of 17 leading U.S. retail chains that account for 65 percent of the U.S. market (Clements & Ohashi, 2005).

We supplement these data with game-specific characteristics such as minimum and recommended hardware requirements. This information is drawn from Gamespot, an online gaming community primarily providing reviews and previews of video game related issues.

In addition, we employ a dataset from Futuremark, the leading company in 3D, PC and mobile performance benchmarks. Futuremark not only sells 3D benchmarks, but also provides a free version for measuring the 3D graphics performance of gaming PCs. This dataset provides roughly 1.5 million benchmark results from four different benchmarks[6]. This information includes not only the benchmark score and the date, but also system specifications such as CPU speed, processor type, graphic card and graphic memory, as well as operating system. We use this dataset to predict average system availability for every point in time between March 2001 and March 2010. Moreover, it gives a clear indication of technological change.

Since the four different benchmarks use different methodologies to calculate the benchmark score, the values need to be standardized. We therefore use an OLS regression with the 3DMark2001 benchmark score as our dependent variable and processor speed, graphic card vendor and graphic card memory as our covariates[7].

These coefficients are then used to predict the benchmark scores of the three remaining benchmark datasets on a 2001 basis, yielding a time-consistent dataset with comparable benchmark values. In a

[5] The NPD database has already been used for several other studies (Shankar &Bayus 2003, Clements &Ohashi 2005, Corts& Lederman 2009, Claussen et al. 2010)

[6] These are 3DMark2001, 3DMark2003, 3DMark2005 and 3DMark2006

[7] The reason why we cannot control for other variables (such as graphic card type) is that we have to use the least common denominator between the benchmark information and the game-specific system requirements. For the most part, they include only processor speed, hard disk space, graphics memory and RAM. The latter is, however, not reported in the 3DMark2001 data.

second step, the coefficients are used to calculate a required benchmark score for the computer games, using the minimum system requirements[8]. In addition, we calculate the monthly system availability on the consumer side as the average benchmark scores of computers benchmarked within the last 12 months[9]. With benchmark data starting in March 2001, we can compute an indicator for game quality for all games released since February 2002.

5.2. Variables and Descriptive Statistics

5.2.1 Revenue (ln)

Our dependent variable is the success of the computer game, measured as the natural logarithm of a game's revenue. Using the natural logarithm, we can reduce the skewness of the revenue data.

5.2.2 Technological Quality

The technological quality $\boldsymbol{TQ_{i,t}}$ of a game which is calculated as follows:

$$TQ_{i,t} = \frac{SYSTEM\_REQUIREMENTS_i}{mean(SYSTEM\_AVAILABILITY_t)}$$

The Futuremark dataset provides benchmark scores by dates, which are then used to calculate a measure for the average hardware configuration by month[10]. To obtain a measure of technological quality, we divide the game's system requirements, expressed as a 3DMark2001 benchmark score, by the average benchmark score of the market. This yields a percentage indicating how much of the available system potential is used by the game in a given month *t*. Since the game requirements do not vary over time, technological quality decreases as the benchmarked hardware gets more powerful. An example of the development path can be found in Figure 1.

5.2.3 Control Variables

While the use of game-fixed effects already captures all time-constant game-specific effects, we still control for some time-variant variables.

Evidently, a tremendous part of sales development can be explained through the time a game is on the market. In our sample, the average game makes roughly 80% of its entire revenue within the first 12 months after release, which is in line with the findings of Deszö, Grohsjean and Kretschmer (2010). Therefore, we control for the time a game is available on the market ($\boldsymbol{age_i}$), defined as the the number of months since the date of launch.

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[8] The coefficient "ATI graphic card" is used for the calculation of the required benchmark score.
[9] We only kept one observation per user per month in order to avoid unsystematic biases.
[10] We use a rolling window of 12 months, considering all users who ran the benchmark within that time span a potential consumer.

Also, we use 12 dummies to identify the effect of the respective calendar month (***dm***). With sales peaking during the holiday seasons, it is important to control for the impact of a particular calendar month on sales. In addition to that, we use year-and genre-fixed effects.

Since technological advancement is also expected to impact sales, we control for detrended technological change $\boldsymbol{TP_t}$ measured as the excess of monthly average change of hardware availability on the market.

We further control for the logaritmized count of developers $\boldsymbol{DC_i}$ engaged in the creation of the computer game, as this variable is expected to significantly drive development costs. In addition to that we control for a vector of dummies including whether the game is part of a series, uses licensed content or employs a 3D-graphic-engine.

5.2.4 Descriptive Statistics

Table 1 gives descriptive statistics of the main variables of interest[11] and Table 2 reports the respective correlations.

The monthly logarithmized revenue ranges between 0 and 16.87, which equals roughly $21 million. The average game in our sample generates roughly $10,300 a month and addresses a market potential of 93%.

INSERT TABLE 1 HERE

INSERT TABLE 2 HERE

Looking at the statistics of $\boldsymbol{TQ_{i,t}}$, it is noticeable that the average game uses only 39% of the available hardware on the market at the time of release. However, this might be the result of two contrary biases. First, the system requirements that we use are the minimum hardware requirements for the calculation of $\boldsymbol{TQ_{i,t}}$. Clearly, recommended hardware requirements are significantly higher but are not consistently available in our sample. Second, graphic benchmarks are, by assumption, most intensively used by hardcore gamers or, put differently, at least not by the standard PC user,

[11] Here, only first-month technological quality is reported because ongoing technological progress would otherwise cause a downward bias.

resulting in a considerable upward bias. However, with both biases being systematic, they do not falsify our results.

6. Estimation and Results

6.1. Empirical Models and Estimation Methods

6.1.1 The Effect of Quality on a Game's Total Success

In our first regression we want to identify the effect of technological quality on the total success of a game. We therefore use the revenue of the first 24 months as an indicator of the game's total success. In our dataset, the average game made 97.4% of its total revenue within the first two years.

We use the following standard OLS regression model with robust standard errors:

$$Log(Total_{Rev})_i = \alpha_0 + \alpha_1 TQ_i + \alpha_2 TQ^2{}_i + \alpha_3 X_i + \sum_{g=1}^{6} \beta_g dg + \sum_{m=1}^{6} \beta_y dy + \sum_{k=1}^{12} \gamma_m dm + u_i$$

The variable $\boldsymbol{X_i}$ is a vector of multiple control variables that are all expected to drive the success of the game. Besides the linear term for technological quality, we also control for the squared value to check for a potentially non-linear relationship. Further we employ dummies to control for potential year- (***dy***), genre- (***dg***) and calendar-months effects (***dm***).

6.1.2 The Effect of Quality in a Dynamic Setting

This estimation seeks to find the effect of different parameters on the monthly revenue[12]. We are particularly interested to see how sales are moderated by technological change.

We use the following specification

$$Log\left(Rev_{i,t}\right) = \alpha_0 + \alpha_1 age_{i,t} + \alpha_2 TP_t + \alpha_3 TP_t * TQ_i + \sum_{m=1}^{12} \beta_m dm + u_i + \varepsilon_{i,t}$$

We use an interaction term to find out how the effect of technological quality is moderated by technological change. Again, we control for calendar months to account for the seasonality of sales. In addition to the standard error term $\varepsilon_{i,t}$, the use of game-fixed effects includes a game-specific time-constant heterogeneity term u_i.

[12] We start with the second month as first month-revenues are not comparable due to different introduction times.

6.2. Results

6.2.1 Quality and Success

Column 1 of Table 3 presents the OLS estimation results of the control variables on the total logarithmized revenue.

INSERT TABLE 3 HERE

Here, we find positive and highly significant coefficients for teamsize and the series dummy (not reported). Not surprisingly, we find sales in December to be considerably higher (not reported) than in other months and highly significant as well.

In Column 2, we add the measure of technological quality. The effect of the variable is positive but insignificant. However, the covariate becomes highly significant in the third column, where we add a quadratic term of technological quality. The coefficient of the quadratic term is negative and significant, indicating a decreasing marginal effect of technological quality on the success of a computer game.

While all control variables remain qualitatively constant, technological change, although still positive, becomes insignificant.

6.2.2 Quality and the Product Life Cycle

Table 4 contains the results for our fixed-effects panel regression. Here, we find several interesting results: First, not surprisingly, the effect of age is significant and negative, meaning that games sell less the longer they are on the market. Second, the effect of technological change is also negative and significant. However, the interaction term for technological change and technological quality is positive which indicates that technological change is not generally detrimental to sales but can be positive if technological quality is sufficiently high.

INSERT TABLE 4 HERE

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7. Discussion

7.1. Technological Quality and Product Success

The results indicate that games with higher technological quality are more successful in terms of generated revenue. Clearly, this sounds fairly intuitive. However, it understates the effect of quality-induced exclusion of consumers.

In the computer game industry, developers need to consider two contrary effects when choosing product quality. First, higher (technological) game quality leads, ceteris paribus, to increased product attractiveness and, second, reduces market potential. This is because more sophisticated graphical effects imply higher system requirements, which exclude consumers whose hardware configuration does not meet the requirements. Our results suggest that, in the case of this particular industry, the sales-enhancing effect of product attractiveness exceeds the negative effect of reduced market potential; however, only to some extent. As expected, we find a decreasing marginal effect of quality suggesting an inverted U-shaped relationship for quality and demand.

This finding implies several challenges for developers. First, since game development can take up to several years, forecasting hardware availability is fairly demanding. Second, even if developers program a game for a computer system that is cutting-edge at the time when development starts, the system requirements might eventually only be average at the time when the game is released. Third, is seems like a fair assumption that the exact system requirements are a by-product of the game development process rather than a deliberately chosen variable.

However, it is not too surprising that we cannot find a single game in our sample that would be of such high technological quality. Firstly, as costs rise at an increasing rate with quality, producing cutting-edge games is extremely costly. Evidently, development costs for video games increased drastically during the last decade and nowadays, the average development budget for a multi-platform game sums up to an eight digit figure. Secondly, with sunk costs that high, publishers are searching for strategies to lower the risk of flopping. A fairly safe way for this is to increase market potential by lowering system requirements, even if by doing so technological game quality suffers.

7.2. Technological Quality in a Dynamic Setting

Our results reveal an interesting (second) trade-off. First, the effect of ***age*** is negative. This is not really surprising as games are heavily advertised during the early months. As expected, the effect of technological quality is negative. That is because, as technology advances, better products are released. For older products it therefore becomes increasingly difficult to attract consumers.

On the other hand, our results show that technological change can has have a positive effect as it increases market potential. This effect is particularly relevant for games with very high technological quality. For those, the initial market potential is fairly limited as the high system requirements exclude a large proportion of potential consumers. As technological change improves average hardware availability (because individuals replace old PCs with new ones), market potential increases for the game.

In conclusion, the developer has to make a choice of whether he prefers a fast start with tremendous sales (then low technological quality would be the best choice) or rather a moderate start and a longer time with above average sales instead.

8. Concluding Remarks

In this paper we investigate the effect of technological quality on the success of computer games, using data from 406 games over the 2002-2008 time period. Our regressions have uncovered a number of interesting findings. First, we find that computer games with higher technological quality generate more revenue. However, the decreasing marginal effect suggests an inverted U-shaped relationship for quality and demand. Second, technological change has two effects on sales: a negative one because better substitutes are introduced and a positive one because it increases market potential. The results show that if technological quality is sufficiently high, the market potential increasing effect outweighs the negative effect of substitutes.

However, it should be pointed out that more research is needed on the relationship of the requirement of a complementary good and product success. While our first study yields preliminary results on this relationship, insight into different industries would be interesting. Especially because the computer game industry does not provide such a strict exclusion like, as an example, a golf course with the handicap requirement. This means that gamers, if they are willing to accept some stuttering, can play a game even if their hardware provides less computing power as required. Therefore, whether our results hold in general can only be explored by a large-scale research, which we hope to have inspired with our paper. More research on this topic would clearly help to provide firmer conclusions.

Our paper has a number of limitations. First, while total game-specific advertising budgets are captured in the game-specific error term due to the game-fixed effects regression, it would be fairly interesting to explicitly include monthly advertising expenditures. Especially during the time after launch, these are expected to drive sales significantly. Second, the results on the height of technological quality might be overstated. That is due to two contrary biases. On the games side, we have a downward bias because for the vast majority of games in our dataset only provides information on minimum system requirements. Clearly, in order to enjoy the game, more powerful hardware is recommended. At the same time we assume an upward bias in our benchmark data. Benchmarking computer systems is especially common in the gaming community where computer power is above average, while the standard personal computers, which might also be used for gaming, are underrepresented in the benchmark dataset. Indicators for the upward bias are observations of CPUs with 22 GHz, which is an unmistakable sign for overclocking, which, again, is an idiosyncrasy of the gaming community. However, since these biases are systematic they do not make our findings less valid. Third, although game sales are a first indicator, a game's profits would be a far more reliable sign of product success. However, our dataset lacks information on development costs or, at least, development time, which in combination with teamsize could be used as a proxy. This would be a promising topic for further research.

Despite these shortcomings, we believe that our paper provides useful insight on the relationship between the requirement of complementary goods and product success, thus lending some empirical support to quality-setting strategies of computer game developers.

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Figures and tables

Table 1: Summary Statistics

Variable	Mean	Std. Dev	Min	Max	N
Revenue (ln)$Rev_{i,t}$	9.212	2.479	0	16.873	9,252
Technological Quality $TQ_{i,t}$	.392	.160	.17	1.170	9,252
Technological Change TP_t	-.0319	.270	-.362	.777	9,252
Teamsize TS_i	121.65	102.40	1	843	406

Table 2: Pairwise-correlations

Variable	(1)	(2)	(3)	(4)
(1) Revenue (ln) $Rev_{i,t}$	1.000			
(2) Technological Quality $TQ_{i,t}$	0.509	1.000		
(3) Technological Change TP_t	-0.108	0.090	1.000	
(4) Teamsize TS_i	0.358	-0.006	-0.094	1.000

Table 3: Regression Results (Dep. Var: First 24 Months Revenue(ln))

Variable	(1)	(2)	(3)
Tech. Quality TQ_i		0.984	7.117**
		(0.815)	(2.688)
Tech. Quality squared TQ^2_i			-5.249**
			(2.048)
Teamsize (ln)	0.567***	0.551***	0.519***
	(0.138)	(0.140)	(0.141)
Series Dummy	yes	yes	yes
Licensed Content Dummy	yes	yes	yes
Special Technology Dummy	yes	yes	yes
3D-Engine Dummy	yes	yes	yes
Genre	yes	yes	yes
Calendar Month	yes	yes	yes
Year	yes	yes	yes
Estimation Method	OLS	OLS	OLS
Observations	356	356	356
R-squared	0.319	0.322	0.330

*p<0.1, **p<0.05, ***p<0.01; robust standard errors in parentheses

Table 4: Regression Results (Dep. Var: Revenue (ln))

Variable	(1)
age	-0.118***
	(0.009)
Tech. Change	-0.696***
	(0.229)
Tech. Change*Tech. Quality	1.019**
	(0.491)
Calendar Month	Yes
Estimation Method	FE
R-squared	.709
N (obs)	9,252
N (games)	406

*p<0.1, **p<0.05, ***p<0.01; robust standard errors in parentheses

Figure 1: Development of Graphics Memory and Benchmark Scores 2001-2010