Optimal Price Strategy

For the Sellers in the Steam Market

by

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**Abstract**

The market of PC games has several features that make it different from a market selling concrete goods. The goal of this paper is to suggest an optimal price skimming strategy for the sellers of digital games in a particular PC game market (Steam) based on certain assumptions of the product demand, and see if there is some empirical evidence from the real pricing data supporting such strategy. This paper has proved that when facing a linear or concave demands consist of sophisticated consumers, the monopolist cannot gain more revenue by conducting a multi-stage price skimming, compared to the revenue obtained by sticking to the (single-period) monopolistic price. The optimal pricing strategies under mixed consumers and dynamic settings are also discussed in this paper. The results indicate that the current price strategies carried out by the sellers on Steam can be optimal under certain assumptions.

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I would like to dedicate my work to Siming Ye, as a compensation for not replying her message during the writing.

Optimal Pricing Strategy for the Sellers in the Steam Market

**I. Introduction**

Steam, a “digital content distribution channel” (Valve, n.d.), is a fast-growing platform that mainly delivers various digital games to global PC game players who are seeking interesting games to purchase. The Steam creates a market that allows numerous digital games developers to sell their games in this platform, which has the following features: (1) there is no perfect or even partial substitute for a particular PC game: even variants of *Tetris* can be differentiated both horizontally (e.g., the appearance of geometric shapes) or even vertically (e.g., differences in gameplay); (2) each game sold in Steam market can be distributed at almost zero marginal cost, since the products are merely digital copies of the game; (3) there exist fan consumers for a particular game (who are willing to pay higher price only because of the “brand name” of the game) and normal consumers who do not have extra willingness-to-pay for a particular game; (4) the sellers on the Steam are allowed to set huge discounts on their products (up to 90%), so they have a wide range for adjusting the price of their products; and (5) there are multiple annual grand sales in Steam, which help the consumers to build their expectations on future discounts on the games that they are interested in. Also, most of the digital games sold on Steam charge the player a fixed price for buying the game itself, as a traditional way in doing the business in the game industry (Marhcand and Hennig-Thurau, 2013). It is very natural for each seller on the Steam market to think about one simple question: how should I design a price schedule, as a sequences of price in different time slots, for my new product that is going to be launched in Steam, so as to maximize my profits? Surprisingly, despite the huge revenue (roughly $4.3 billion in 2017) and substantial market share (at least 18% share of the entire digital PC game market in 2017) that Steam has captured (Bailey, 2018), there is no previous literature investigating the optimal pricing strategy for the sellers in the Steam market[[1]](#footnote-1). Only when we expand our scope to the entire game industry, there are literatures on overall industry organization (Kerr, 2006) and marketing strategies (Ahmad et al., 2017), instead of particular pricing strategies.

On the other hand, ever since the 1950s the optimal pricing strategy for a new product (with advanced techniques or other features such that there is no substitute in the current market) entering a market has received much attention from academia. The work of Joel Dean (1950, 1976) has argued that the seller should choose his or her pricing strategy from either price skimming or penetration pricing, i.e., there is a trade off between exploiting more profits from consumers with high willingness-to-pay by setting a relatively high initial price (price skimming) and selling more products to consumers in a short period of time by setting a relatively low initial price (penetration pricing) faced by the seller. In the subsequent research articles, the particular pattern of dissemination of the new product is also studied and improved to generate “either a monotonically decreasing pricing pattern or an increase-decrease pricing pattern” that is in line with the empirical data in the colour TV (monotonically decreasing) and clothes dryers (increase-decrease) market (Krishnan, Bass and Jain, 1999). Several important features of the market supporting price skimming (rather than a penetrating price) include a group of inelastic consumers who are willing to pay relatively high price for the particular product, and the high monopolistic power of the seller in the market, which are highly similar to the market features we have in Steam. Based on these market features we have observed in the Steam market, the goal of this paper is to suggest an optimal price skimming strategy for the sellers in the Steam market based on certain assumptions of the product demand, and to see if we can find some supportive empirical evidence from the real pricing data that is in favour of the optimal strategy we have from our modelling work.

The remainder of this paper has the following structure: the next section will introduce basic assumptions of the model and the optimal pricing strategy under: the single-stage selling, the multiple stages with myopic consumers, as well as the discrepancy between the modelling results and the actual pricing strategy in the Steam market; the third section will consider the effect of sophisticated consumers and solve the new optimal pricing strategy under such assumptions, as well as a discussion on the optimal pricing strategy for a mixed group of myopic and sophisticated consumers; the fourth section will consider the optimal price schedule of the monopolist facing a mixed group of fan consumers and normal consumers; the fifth section will provide a brief discussion for the optimal pricing strategy under a dynamic setting; and the sixth section will give a conclusive remark of the modelling results with empirical supporting evidence from the true Steam data, as well as a discussion on the limits of this work, together with possible paths for the future research.

**II. The Basic Model**

In the basic model, we consider a game market with a group of game developers that will independently decide their price schedules, i.e., all the game products in it are unique and cannot be substituted by any other games in the market[[2]](#footnote-2). Therefore, every developer (and seller) of the game becomes a monopolist in the market, and each game will have its own demand function. We further assume that there is no marginal cost for producing additional digital copies of games, and each consumer in the market can at most buy the product once (there is no need to buy the same game for the second time since the Steam allows its user to download and play his or her purchased games on any computer once he or she log in the Steam account). It is also assumed that the consumer group will not change over time, and the seller has the information of the demand function, for the simplicity of the model.

Under the one-stage condition, the seller first sets the price for the product and cannot change it, then each consumer chooses either to buy the product or not to (the consumers act simultaneously) and after all the transactions are completed, the market is closed. Therefore, if the demand function is differentiable, the optimal pricing strategy will be the monopoly pricing, namely, , given that for all P. This optimal pricing strategy will not change even if Steam asks the seller to pay a fixed amount or proportion of the revenue to Steam as the administrative fee.

Now we would like to know under what circumstances would the sellers conduct multi-stage price skimming. Under the multi-stage circumstances, there are finite periods for the monopolist to choose price in each period and for the consumers to choose whether to purchase the product in every period. In the basic model, we assume that all the consumers are myopic: they buy the product once its price is under the maximum of their willingness-to-pay. For a multi-stage price skimming, the seller will design a monotonically decreasing sequence of certain price stages that maximize the profit. The seller always face the trade-off between setting more price “stages” and suffering from the inter-temporal discount factor *0<𝛿<1[[3]](#footnote-3)*. The seller (as a monopolist) can either hold the single-period monopolistic price over the two periods, or set two different prices (assume that ) for the two periods (a two-stage price skimming), and get different revenues:

The seller will conduct a two-stage price skimming if:

The corresponding F.O.C.’s are:

We suppose that for all P. When , it is obvious that ; when , set , then certainly any will lead to a higher total revenue. We now consider a monopolist who has periods to sell his or her product, facing a demand function that will not change over time. Suppose that the monopolist is willing to set a monotonic decreasing price sequence for the periods (instead of sticking on the optimal price for a one-period sale), and the discount factor , there will always it maximizes the total revenue , given that . The exact elements in the sequence are calculated by the backward induction, namely the following set of equations:

Note that here , therefore we have:

The bold indicates that all price levels after are at their values that will maximize the function .

We can get the price elasticity of demand on each price stage that belongs to , namely,

Only when the discount factor , a finite-stage price skimming will start from the monopolistic price (and only has that one price for every period), and as long as , . That is, for monopolists who still care about the future selling their products with a demand function that does not change over time, they will, when conducting a finite-stage price skimming, start from a price higher than the monopolistic price for the first period and gradually lower the price of the product in the succeeding periods.

The consequential inference of this basic model is that as long as , there is no reason for the seller to stop before going to the infinite-stage price skimming: suppose there such that the seller will gain maximum revenue, then the seller can simply add more on his or her revenue by picking an arbitrary and from our assumption the seller will gain . Then the next step will be optimizing the whole price sequence via the set of equations mentioned above and get the same evidence indicating that adding a new price “stage” will lead to more revenue. One solution is to set an actual cost on adding each pricing stage. Then the seller can set the number of price “stages” by picking . However, there is no evidence indicating that Steam will charge a fee to the seller for setting discounts. Also, the empirical pricing data from Steam Database (a third party tool providing price information of the games sold in Steam) do not support the idea that the seller will set as many price stages as possible (see Figure 1 and Figure 2 as two examples). In figure 1, the full pricing history (from its date of launch) of *Nekopara Vol. 1*, the first visual-novel game in the *Nekopara* series, is presented (SteamDB, n.d.a). In figure 2, the partial pricing history of *Sid Meier’s Civilization V* (released in September 2010), the fifth turn-based strategy game in the *Civilization* series, is presented (SteamDB, n.d.b).

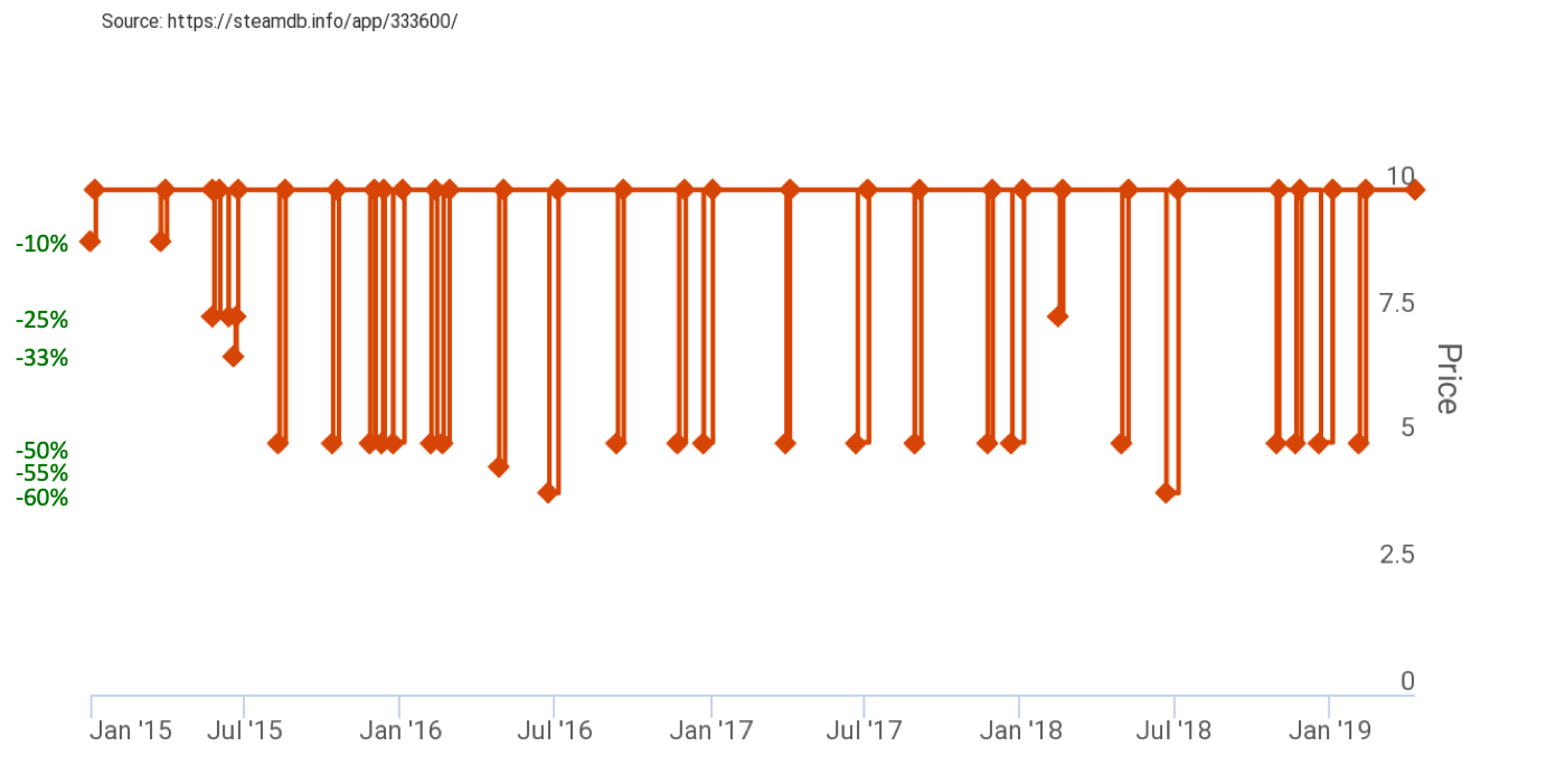


Figure 1: Full Price Schedule of the Digital Game *Nekopara Vol. 1* (SteamDB, n.d.a)

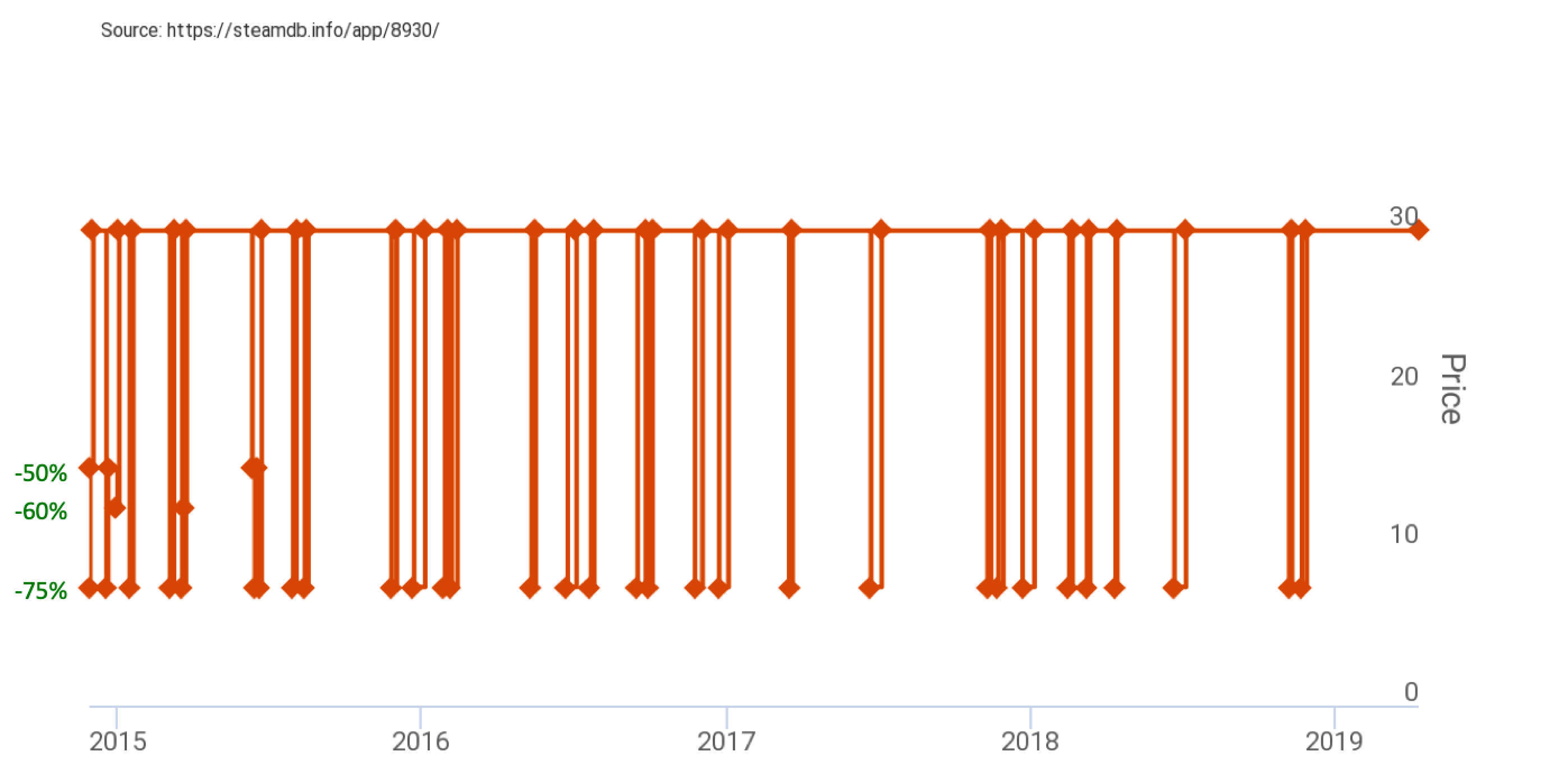


Figure 2: Recent Price Schedule of the Digital Game *Civilization V* (SteamDB, n.d.b)

From these two samples of pricing strategies, we can find three major discrepancies between the optimal pricing schedule we have from the basic model and the real pricing schedule. Firstly, in both examples, the seller only set finite price stages, instead of infinite price stages, and in the example of *Nekopara Vol.* 1 we can also observe a gap between the 25%-33% off price interval and the 50%-60% off price interval, regardless of the 10% discount in the very first period since the game has been released. Secondly, in the example of *Civilization V*, after the game has released for several years, the seller tend to set the same discount (75% off) repeatedly for up to 6 times a year, which will not bring any additional profit under the assumptions of the basic model. Last but not least, we find that sometimes the seller tend to set a launch discount (which will be effective during the first 7 days after the game is released on Steam). Although a launch discount is not necessarily inconsistent with the optimal pricing strategy predicted by the basic model (because the seller can match the discounted price with the first-stage optimal price), its motivation is not well indicated. We would like to fill the gap between the basic model and the empirical data in the following sections.

**III. Price Skimming with Sophisticated Consumers and Mixed Consumers**

In this section, we mainly focus on filling the first half of the first discrepancy between the basic model and the empirical pricing data. That is, why the seller tend to set a price schedule with finite different price stages, instead of (a monotonically decreasing) one with infinite different price stages? It is mentioned above that one major feature of the Steam market is that it has multiple annual grand sales so that the consumers may anticipate future discounts for a game that they are interested. We further assume that there exists a group of sophisticated consumers who are sophisticated enough to infer the monopolist’s pricing schedule and be patient enough to wait until the next pricing stage (or any other following pricing stage) for a greater payoff. For further simplicity of the model, we assume that the consumers have the same discount factor as the one with the monopolist. From the settings of sophisticated consumers in the work of Besanko and Winston (1990), we propose that the sophisticated consumers will only choose to buy the product at the current pricing stage if all of the following inequalities hold:

Here, is the maximum of the willingness-to-pay of one particular sophisticated consumer. From the previous results, it is clear that at period , all the consumers with a willingness-to-pay no less than the current price will buy the product at period , so as the total demand at period . The difference between the total demand at period and period indicates the number of consumers who would like to purchase the product at period . When , i.e., when the market consists of only myopic consumers, the optimal price schedule for a multiple-stage price skimming indicates that:

Plug in the equation above (as well as its recurrent form), for any we will have the following condition for the sophisticated consumers to purchase at price stage :

Let to be the minimal willingness-to-pay that a sophisticated consumer should have to purchase the product at price stage :

The characteristics of sophisticated consumers have determined that if the monopolist set two price stages too close to each other, the latter one can be “ineffective”, i.e., there will be no sophisticated consumer who would like to buy the product at that particular price stage. For a price stage to be “ineffective”, the following inequality should hold:

It is clear that for any price stage , given that there is no “ineffective” price stage in the price schedule, all sophisticated consumers who have the maximum of their willingness-to-pay larger than will purchase no later than the price stage

From the previous price schedule, we would like to determine whether price stage is “ineffective”:

Note that by the Mean Value Theorem (M.V.T.)[[4]](#footnote-4), given that is continuous. We can only conclude that a necessary condition for the price stage to be “ineffective” is that . The difference between and can be regarded as a cost for setting a price schedule, and thus can offset the additional revenue obtained by the monopolist via setting more price stages into the price schedule. Suppose that the monopolist want to add another price stage to the exiting price schedule, , the change in the profit will be:

Here is the minimal willingness-to-pay a sophisticated consumer should have to buy the product at period after a new (and lower) price stage is added by the monopolist at period . For the additional profit to be positive, we need:

Note that if , then and . That is, there will be no need for forming multi-stage price skimming under a concave or linear demand function if all the consumers are sophisticated, and the optimal price strategy for the seller will be sticking on the monopoly price for all the stages.

However, when the monopolist is facing a mixed group of consumers that includes not only sophisticated consumers but also myopic consumers, multi-stage price skimming can still be the optimal price strategy. For a general setting, assume that share of the total consumers are not sophisticated and share of the total consumers are sophisticated. Also, assume that myopic consumers and sophisticated consumers are evenly distributed at each level of the willingness-to-pay (e.g., if there are myopic consumers at , as their maximum willingness-to-pay of the product, there will be sophisticated consumers at the same level of ). When decreases the monopolist will be able to set a finite-stage or an infinite-stage monotone decreasing price schedule more than 2 stages. The exact threshold of cannot be calculated without an explicit demand function. Still, from the following proof, it is able to show that given any , there exists some “space” for a finite-stage price schedule that has more than 2 price stages under a concave or linear demand. Consider the additional profit brought by adding a new price stage based on an “effective” price stage , and the monopolist will add a new price stage if such additional profit is positive:

Here .

Note that if , then and . Also, , so as long as , there exists some “space” for a finite-stage price schedule that has more than 2 price stages under a concave or linear demand. When increases, which means there are more myopic consumers among the consumer group, the seller will be able to set more price stages to increase the revenue.

Overall, after considering the effect of a certain proportion of sophisticated consumers, the monopolist will no longer set an infinite-stage price-skimming schedule because the existence of sophisticated consumers will work as a cost for the monopolist to add another price stage in his or her price-skimming schedule. Therefore, we conclude that the first half of the first discrepancy between the basic model and the empirical price data can be explained by the existence of sophisticated consumers among the consumer group.

**IV. Price Skimming with Fans and Normal Consumers**

In this section, we mainly focus on filling the second half of the first discrepancy between the basic model and the empirical pricing data. That is, why is there a gap between the two price intervals that have multiple close price stages respectively? The sophisticated consumers will either lead to either one-stage monopoly pricing (if all or most of the consumers are sophisticated) or multiple-stage price skimming, but cannot explain the huge pricing gap. From our previous observation of the Steam market, we have discovered that there are fan consumers who are willing to pay higher price for a particular game merely because of the “brand name”. Therefore, if all the fan consumers are clustering around a higher price as their maximum willingness-to-pay and the rest (normal consumers) are clustering around a lower price, with a substantial gap between the higher and lower prices, it is probably that the overall demand function of the game will no longer be concave or linear, and the optimal price schedule we have from our basic model will not be optimal anymore[[5]](#footnote-6). This statement is at least true if the demand functions that are “sufficiently convex”, i.e. , for in at least one price interval (e.g., the substantial gap between the price fan consumers clustering and the price normal consumers clustering): the seller may want to set a price schedule with a gap between two price intervals that have multiple close price stages respectively (we call this price strategy “the double price skimming with a price gap in-between”). Consider the simplest case that for and for , , and the consumers are *not* sophisticated (so they will buy the product once the current price is lower than the maximum of their willingness-to-pay). That is, most of the fan consumers are willing to pay more than times the price compared to the normal consumers. The seller will only consider price skimming if . From the same procedure, we are able to get and to maximize the revenue, where . The seller wonder if there is a need to apply price skimming in period 1 before set the optimal price (in period 2):

The condition for a seller to apply the double price skimming is clear:

A sufficient condition for the double price skimming strategy to occur will be:

Note that a sufficiently large will eventually trigger the application of the double price skimming with a price gap in-between. Practically, if the seller observes a minor increase of buyers after a moderate sale, and the marginal increases of buyers are similar when slightly adjusting the prices clustering around the two prices (the original price and discounted price), one should apply the price skimming. Specifically, consider two identical “peaks” in the probability density function of the consumer demand that will lead to , then we should expect at the two different price levels. That is to say, for a typical product with such a high markup that the seller decides to price discriminate between fan consumers and normal consumers, we should observe higher price elasticity of demand.

Apart from the situation that has been discussed above, we would like to consider the impact of sophisticated consumers in conducting the double price skimming with a price gap in-between. In the previous section we proved that there will be no multi-stage price skimming under any concave or linear demand function when the monopolist is facing sophisticated consumers, so there will be no multi-stage price skimming in the concave part of this demand function. Suppose that the consumers are going to pick from the two single-stage optimal price stages: and , as indicated in the above model. In order to simplify the notation, we rename them as and . From the earlier settings, it is clear that only the consumers holding a large will buy the product at the initial pricing stage:

The condition for launching a price skimming is:

Suppose that , we have as a necessary condition for only charge the high-type consumer and as the condition for conducting a two-stage price skimming at an interval of time slots. Similarly to the situation with all myopic consumers, we conclude that a sufficiently large will eventually trigger the application of the double price skimming with a price gap in-between. Therefore, the second half of the first discrepancy between the basic model and the empirical price data can be explained by the existence of two groups of consumers who are interested in the particular game, namely fan consumers and normal consumers that have a huge gap between their maximum willingness-to-pay for the particular game[[6]](#footnote-8).

**V. Price Skimming with Dynamic Settings**

In this section, we mainly focus on filling the second discrepancy and the third discrepancy between the basic model and the empirical pricing data. Namely, why the seller tend to always set the same discount rate in each discount for a game that has been released to the Steam market for a long period of time, and why some sellers would like to set a launch discount, and others do not? To answer these questions, we need to first build a simple dynamic setting, in which we assume that there is a natural increasing rate that applies to the entire demand function. Therefore, . If there is positive profit after adding a new price stage, we will need:

Let , , we will have since and , and the rest of the proof for a negative additional profit goes naturally. Thus, the addition of a natural increasing rate, as long as it applies to the entire demand function, will not affect our conclusion that when facing sophisticated consumers there is no need for forming discrete price discrimination under a concave or linear demand function. From this conclusion, we can argue that the second discrepancy between the basic model and the empirical pricing data, i.e., the same discount rate for each discount after the game having been released for a long period of time is due to the increase of the normal consumers whose maximum willingness-to-pay is clustering around a price significantly (say 75%, for example) lower than the original price over time.

In order to give possible motivation for the seller to set a launch discount, we would like to first prove that a launch discount will at least do no harm to the sales in the static settings, and then elaborate why some sellers would love to set a launch discount, and others do not in the dynamic settings (in which a natural increasing rate applies to the entire demand function over time). The launch discount has the following features: it is often 10% or 15% and it will start at the same day when the publisher releases the game. Since there is no price history for the game, and the consumer will not expect a second launch discount (because it is technically impossible), we assume that all sophisticated consumers will purchase the game if . The publisher will set a launch discount if:

Here is the increase rate in demand due to the information of launching a discount.

One way that can ensure a higher profit is to set (the discounted price) such that , then the profit will certainly be higher even if (and at the optimal when facing a pure group of sophisticated consumers).

Then why some of the publishers are not willing to set launch discounts? This is because the Steam has ruled that the launch discount can only last 7 days after the release of the game, but needs 30 days after the entire discount period for the publisher to set another discount. If we consider the entire situation in a dynamic setting, then the trick above (set the discounted price at the level of the optimal single-period price) will not guarantee a higher revenue via setting a launch discount: if the “natural” increasing rate in demand is high for one game, then launching a discount may cause a mismatch between the origin price and the optimal single-period price, which will cause loss afterwards. The decision on whether to set a launch discount will depend on whether the increase in the consumers (attracted by the information of the launch discount) is sufficiently high to bring higher revenue compared to not having the launch discount: , given that .

**VI. Concluding Remarks**

The modelling work presented in this article has indicated that the current price strategies of the sellers on steam *can be* optimal, and the number of stages, intervals between two price stages, as well as whether a launch discount is set reveal several key features in the demand functions or the distribution of different types of consumers of that particular game. Specifically, it is important to keep in mind that in reality the seller will never have a perfect information about the demand function, therefore it is more proper to say that the exact price schedule one has selected represents his or her *belief* about the demand function of his or her product. In particular, if the seller choose to set more price stages in the price schedule, he or she is likely to believe that a greater proportion of consumers demanding the product are myopic instead of sophisticated. Since in the model we have assumed that the consumers and the monopolist share that same discount factor, it is also reasonable to say that the seller believes that most of the consumers have a much lower discount factor than the seller when more price stages are designed into the price schedule. Besides, if the seller set two price stages with a huge interval in-between, then the seller probably believes that there are substantial number of fan consumers of this particular game that are sufficient for discriminating between fan consumers and normal consumers, who have different willingness-to-pay for the same game. Also, if the seller set more price stages for fan consumers than for normal consumers, then it is likely that the seller believes that more proportion of the fan consumers are myopic, compared to the proportion of myopic consumers among normal consumers, or that fan consumers are less “patient” in waiting for a lower price than the normal consumers. What's more, the choice of whether to set a launch discount reveals the seller’s believe in the dissemination pattern of the game: does most of the fan consumers tend to be attracted at the first several days after release (in which the seller prefers a launch discount), or there will be a continuous increasing in the core player base (in which the seller prefers to release the game at its original price)? Although currently no reliable sales data for the Steam market is available for us to verify some of the inferences we have got from the model, it is reasonable to argue that even if the seller does not have full information at first, he or she, given an *ex ante belief* on the type of demand function (e.g., linear function, Bass function, etc.), is able to adjust his or her pricing schedule after more information on the market performance of the game is available months after the release.

Despite the fact that the results we have obtained from the modelling work is generalizable to all the concave or linear demand function, there remain some differences between the assumptions of the model and the actual market conditions we have, which may change the predictions of the model. First of all, in the model we assume that the seller is able to hold the price in each price stage but in fact the seller in the Steam market can only launch discounts to adjust the game price. In accordance with the discount policy in Steam, the period of each discount should be no more than 7 days, including most of the major seasonal sales (Kain, 2017) and the sellers cannot launch new discounts within 2 months from the last discount under most circumstances[[7]](#footnote-10) (Steam, n.d.). This discrepancy between the assumption and actual policy will not affect the optimal pricing strategy under a static demand and a highly efficient market, but may change the optimum under the dynamic settings. Secondly, in the model we assume that each seller can perform as a monopolist in the Steam market, which is not true: although there is no full substitute in a game market, partial substitutes certainly exist at least among some series games (e.g., *Civilization IV*, *Civilization V*, and *Civilization VI*); for other series games, they are like complements (e.g., *Nekopara Vol. 1* and *Nekopara Vol. 2*; very few will buy *Nekopara Vol. 2* without buying *Nekopara Vol. 1* because the story is consecutive). The current model needs to be improved to include the effects between games in the market. Besides, the sellers in the Steam market can choose to offer bundlings to the consumers, which may also leads to other optimal selling strategies (Prasad, Venkatesh and Mahajan, 2017). Last but not the least, the current model assumes almost infinite “commercial life” for each game in the market, which can be reasonably challenged. It is true that unlike fast moving consumer goods, classical games sometimes remain popular even decades after their release date, but for most of the games, they have relatively short commercial life. Nevertheless, the predictions under static demands will not change with the commercial life of the games, and can be always used as a starting point of the life-cycle analysis of games in the Steam market.

There are also several interesting questions that have not been fully considered in this article and are worth studying in the future research. Firstly, it is not clear how exactly will the consumers formulate their maximum willingness-to-pay for a particular game. Although there exist some literatures investigating the purchase motivation (Hamari et al., 2017), more empirical research is needed before we can fully understand the consumer behavior. Secondly, in this article, when considering the effect of sophisticated consumers, we assume that the monopolist commits to a preannounced price schedule, so that the sophisticated consumers can choose the optimal price stage to purchase accordingly. However, it is also possible that the monopolist can determine the future price contingent upon the sales at current price (responsive pricing), since the Steam market also have a review system that can provide extra information to both sellers and consumers after the game is released. It will be promising to consider this possibility in the future research and to compare the optimal pricing strategy under responsive pricing and the optimum under preannounced pricing, given the fact that several studies have already step into this area (Papanastasiou and Savva, 2017).

References

Ahmad, N. B., Barakji, S. A. R., Shahada, T. M. A., & Anabtawi, Z. A. (2017). How to launch a successful video game: A framework. *Entertainment Computing*, *23*, 1–11.

Bailey, D. (2018). *With $4.3 billion in sales, 2017 was Steam’s biggest year yet.* Retrieved from https://www.pcgamesn.com/steam-revenue-2017

Besanko, D., & Winston, W. L. (1990). Optimal Price Skimming by a Monopolist Facing Rational Consumers. *Management Science*, *36*(5), 555-567.

Buxmann, P., Strube, J., & Pohl, G. (2007). Cooperative Pricing in Digital Value Chains - the Case of Online Music. *Journal of Electronic Commerce Research*, *8*(1), 32–40.

Dean, J. (1950). Pricing Policies for New Products. *Harvard Business Review*, *28*(6), 45–53.

Dean, J. (1976). Pricing Policies for New Products. *Harvard Business Review*, *54*(6), 141–153.

Hamari, J., Alha, K., Järvelä, S., Kivikangas, J. M., Koivisto, J., & Paavilainen, J. (2017). Why do players buy in-game content? An empirical study on concrete purchase motivations. *Computers in Human Behavior*, *68*, 538–546.

Kain, E. (2017). *Dates For The Next 3 Steam Sales Have Leaked Online.* Retrieved from https://www.forbes.com/sites/erikkain/2017/10/21/dates-for-the-next-3-steam-sales-have-leaked-online/#6b986a464d97

Kerr, A. (2006). Digital Games as Cultural Industry. In *The business and culture of digital games. Gamework/Gameplay.* Retrieved from http://mural.maynoothuniversity.ie/2121/

Krishnan, T. V., Bass, F. M., & Jain, D. C. (1999). Optimal Pricing Strategy for New Products. *Management Science*, *45*(12), 1650-1663.

Marchand, A., & Hennig-Thurau, T. (2013). Value Creation in the Video Game Industry: Industry Economics, Consumer Benefits, and Research Opportunities. *Journal of Interactive Marketing, 27*(3), 141-157.

Papanastasiou, Y., & Savva, N. (2017). Dynamic Pricing in the Presence of Social Learning and Strategic Consumers. *Management Science*, *63*(4), 919–939.

Prasad, A., Venkatesh, R., & Mahajan, V. (2017). Temporal product bundling with myopic and strategic consumers: Manifestations and relative effectiveness. *Quantitative Marketing & Economics*, *15*(4), 341–368.

Steam (n.d.). *Discounting.* Retrieved from https://partner.steamgames.com/doc/marketing/discounts

SteamDB (n.d.a). *NEKOPARA, Vol. 1*. Retrieved from https://steamdb.info/app/333600/

SteamDB (n.d.b). *Sid Meier’s Civilization V*. Retrieved from https://steamdb.info/app/8930/

Valve (n.d.). *At Valve we make games, Steam, and hardware.* Retrieved from https://www.valvesoftware.com/en/about

Weyl, E. G., & Tirole, J. (2012). Market Power Screens Willingness-to-Pay. *Quarterly Journal of Economics*, *127*(4), 1971–2003.

1. For similar markets (e.g. App Store or iTunes), there are articles investigating best pricing strategy for the platform to increase revenue under the cooperation of other actors in the value chain (Buxmann, Strube and Pohl, 2007), or best rewarding system for the platform to encourage innovation among software developers (Weyl and Tirole, 2012). [↑](#footnote-ref-1)
2. For example, each visual novel game can be regarded as unique since each of them (if not plagiarizing) are telling different stories to the players and the consumers purchase them just as buying novels in the book store. [↑](#footnote-ref-2)
3. Suppose that under the current macroeconomic conditions, the risk-free rate of return (over one period) for cash is , then the inter-temporal discount factor for each period is . [↑](#footnote-ref-3)
4. For a continuous function, say continuous on a closed interval , then there exists . [↑](#footnote-ref-4)
5. Here the major difference between fan consumers and normal consumers lies in their willingness-to-pay, which says nothing about whether they are myopic or sophisticated. [↑](#footnote-ref-6)
6. When the maxima of willingness-to-pay of consumers cluster around two different prices that have a huge gap in-between (and are sufficiently concentrate around each price), the demand function of the product will be concave at first, then convex in an interval containing the first price of clustering, then concave, then convex in an interval containing the second price of clustering, and concave at last. [↑](#footnote-ref-8)
7. This two-month interval can be shorter between two discounts if the seller of the game is invited by the Steam team to participate in major sales in Steam (also, if the seller is launching a discount during a major sales that the game will participate, the discounts will be add up). [↑](#footnote-ref-10)