PRICING STRATEGIES FOR ONLINE MULTIPLAYER GAMES

by

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A dissertation submitted to the faculty of
The University of North Carolina at Charlotte
in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in
Computing and Information Systems

Charlotte

2013

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ABSTRACT

NEAL PARKER. Pricing strategies for online multiplayer games.
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This dissertation examines the different pricing strategies available to online multiplayer game publishers. We develop mathematical models of the pricing decision that the publisher engages in and conduct a numerical experiment to identify critical parameters for the pricing decision. We also develop an agent based simulation to further examine the influence of these parameters on the dynamics between the publisher and consumers and make recommendations about the conditions under which certain pricing strategies are superior to others.

DEDICATION

For God and Country

ACKNOWLEDGEMENTS

This dissertation represents the effort of many people. I would like to thank my committee chair and mentor, Dr. Moutaz Khouja, as well as my committee, Dr. Cem Saydam, Dr. Jing Zhou, Dr. Doug Cooper, and Dr. Cliff Scott. I would also like to thank Dr. Ram Kumar, Dr. Dawn Medlin, Dr. Sandy Vannoy, Dr. SungJune Park, and Dr. Chandra Subramaniam. I would like to extend a special thanks to Dr. Sarah Khan. Finally, I would like to thank my family, Don, Diana, Graham, and Byron, for all of their support.

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CHAPTER 1: ONLINE GAMES AND GAMING

1.1 Introduction

It is a long way from the first futile efforts of Ralph Baer in 1949, the start of Atari in 1972, the 8-bit Nintendo of 1986, and the first massively multiplayer online game called Meridian 59 in 1996 all the way up to the technical and financial juggernauts of the console and computer games of contemporary times. What's more, the world of video games is still evolving (Herman, Horwitz, Kent, & Miller, 2002). In the early nineties, industry analysts and scholars were uncertain as to the future of games and game companies (Shapiro E. , 1991); however, video games, specifically online multiplayer games, have seen exponential growth over the past decade. In 2001, sales of hardware and software for game systems rose 43 percent to $9.4 billion exceeding the revenues of Hollywood's box office receipts (Faber, Lee, & Nan, 2004) and such growth has been across the globe (Scanlon, 2007). Activision Blizzard (NASDAQ GS: ATVI), publisher of the largest online game, earned revenues of $3.026 billion in 2008 year, a 120 million dollar increase from 2007. Within some market segments, online games are among the most popular forms of entertainment (MacInnes & Hu, 2007; Huhh, 2008), perhaps as a result of the large increase in broadband and high speed Internet connections (Ulmer, 2004; Jones & Fox, 2009).

Individuals choose to spend both time and money on games for a variety of reasons and the research concerning this adoption and use behavior is still ongoing (Choi

& Kim, 2004; Griffiths, Davies, & Chappell, 2004; Yee, 2006). Rather than view gaming as a subset of "play," it may be possible to treat game enjoyment as an inherent separate activity that is its own social artifact (Malaby, 2007). Among the factors impacting online game enjoyment are the story (or plot), the graphics, the length (as an extension of the natural limits of the plot), and the game's level or type of control or interface (Wu, Li, & Rao, 2008). Players take their gaming seriously. The economics of online multiplayer games are elaborate. The exchange rate between game currencies and national currencies like the US Dollar or the Euro are closely monitored. The game currency in EverQuest makes this virtual environment the 77th wealthiest nation in the world (Lindstrom, 2004) in terms of currency valuation.

Given the fragmented nature of the online game industry, the massive revenue potential that the industry has represented to date, and the difficulties that some entities involved in providing games to consumers, it behooves us to consider various pricing strategies for the different types of games. The following sections provide a motivation for this research effort and provide a review of literature pertinent to the topic at hand. A thorough game classification is followed by a discussion about the attributes or characteristics of games. A description of the video game industry structure precedes a review of the economic factors of game pricing.

1.2 Motivation

This research effort is designed to provide a theoretical framework for the pricing of online multiplayer video games. Given that online games are a relatively new phenomenon and that there is only a limited number of relevant studies on their pricing, development of good pricing models will enable better and faster development of the field, enable greater profits for developers and publishers, promote diffusion of workable pricing models throughout the industry, and lead to better decision making by the involved parties. The goal of this research effort is to provide effective pricing for a relatively new and emerging industry.

As discussed in later sections, pricing is contingent on a number of different factors, many of which are inter-related. Before presenting a model of online multi-player game pricing strategies, it is necessary to answer concerns regarding the classification of online games. Specifically, a logical classification of game types must be determined. The aim of such is to enable models to be generalizable within each class, and to allow conclusions about pricing to be drawn between classes. Such models would be more useful than those efforts which treat all digital experience goods as a single type of purchase.

1.3 Game Classification

An online gamer faces a bewildering array of game types, variations, play styles, themes, and options. No two games are exactly alike, and some, despite sharing code in the form of game or graphics engines, are radically different. Classifications can be made along a variety of factors (Chambers, Feng, Sahu, & Saha, 2005). While virtual worlds have been examined to attempt to fashion a typology (Messenger, Stroulia, & Lyons, 2008), such efforts have been anecdotal in nature and have not been put to any form of test. Throughout the next section, we illustrate critical differences between types of games. These differences make a classification scheme possible as shown in Figure 1.1.

1.3.1 Console vs. PC

Games have historically been grouped into two super categories: those games designed for consoles, and those games designed for PC use. When examining competition within the industry it may also be advisable to include handheld game systems as a separate category (Williams, 2002). Different consoles have different hardware and subsequent generations of games may or may not be backwards compatible, depending on the cost of designing backwards compatibility into both the hardware and the game itself. PC based games make no mention of backwards compatibility. With the PC's ability to load multiple operating systems or alternatively load a game program as an application for an earlier operating system, backwards compatibility is typically assumed as standard. Specialized tools (emulators) may be used for programs from the late 1980's and early 1990's enabling said programs to load on a modern machine.

Since a game must be modified and then compiled to run on each console type independently, and there may be substantial differences between console and PC versions, the hardware itself dictates this first method of discriminating game classifications. While games are frequently released onto multiple platforms, the distinctions between the requirements of each are so great that it behooves us to consider them as being fundamentally different. Also, gamers are typically reluctant to invest in new technology on a regular basis (Achterbosch, Pierce, & Simmons, 2008). Finally, while updates or patches are now possible on some console systems, most PC versions have multiple patches released while this seldom happens for console games (Williams, 2002).

1.3.2 Single Player vs. Multiplayer vs. Massive Multiplayer

Both console and PC games frequently contain the ability for multiple players to challenge each other in one way or another. Single player games are also called "Stand Alone" games (Griffiths, Davies, & Chappell, 2003). Multiplayer play may occur on a single machine, on multiple machines on a single network, or on multiple machines on multiple networks. There are different requirements for both hardware and software for single player as opposed to multiplayer games. Further, these requirements change depending on the method (i.e. single machine vs. single network vs. multiple networks) that is selected for multiplayer play. Games frequently have different load processes for different modes of play as the requirements are so different. Additionally, the use of multiplayer play via multiple networks typically requires game servers which act in such a manner as to connect players or even as far as to actually host the game and make all executions for play on the server side. Many technical obstacles must be overcome to provide a Massively Multiplayer Online Gaming experience (Waldo, 2008). Players report significantly higher levels of enjoyment when competing against human characters or human controlled objects as opposed to computer controlled opponents further supporting the justification of a single versus multiplayer categorization (Weibel, Wissmath, Habegger, Steiner, & Groner, 2008). With the first game to support large numbers of simultaneous users forming a relatively large fanbase (several thousand), the term Massive-Multiplayer became accepted (Achterbosch, Pierce, & Simmons, 2008).

Not all multiplayer games can be considered massively-multiplayer. While America's Army is predominantly a multiplayer game, since it is limited to between two and sixteen players within a single instance of the game, and not the thousands (or tens of thousands) common to typical massive multiplyer online (MMO) games, it is simply a multiplayer game (Nieborg, 2004). MMO games typically have a large enough collection of simultaneous players for the community to form groups. These groups may be official or otherwise, but persistent organizations (guilds, clans, corporations, etc.) are formed to carry out a collective goal (Ducheneault, Yee, Nickell, & Moore, 2007).

1.3.3 Delivery Method

Games may be installed on a local machine by the gamer, or may be accessed via a web interface. In the former case, these games may have been purchased at a retailer or downloaded (legally or otherwise). This latter method is typically only a concern for a PC based game. While numerous delivery methods for games exist, one of the most universally popular has been *Browser-based* games. Such games may be written in Flash or Javascript and may be loaded or accessed by any modern web browser. Browser based games such as Travian and its clones have a high level of appeal due to (like several other types of online games) the ability to socialize with others, compete against others or other groups, low cost (in terms of time) to get started playing, and the ability to escape pressures or receive social support from other players (Klimmt, Schmid, & Orthmann, 2009). Social networking sites such as Facebook have been studied as a delivery method for online games or other network based applications (Nazir, Raza, & Chuah, 2008). This delivery method is somewhat unique among browser based games as it makes use of the powerful effects of network externalities discussed in later sections.

1.3.4 Persistent vs. Nonpersistent States of Play

Both PC and console games, regardless of delivery method, can have either a persistent or a non-persistent state of play. In a persistent play state, the servers have some type of *life cycle* and player attributes and activities are remembered by the server and can change irrespective of whether or not the player is actually active within the game environment. In MMO games, a server (and thereby the accounts on said server) is generally persistent over time (Caltagirone, Keys, Schlief, & Willshire, 2002). Making a game persistent can be difficult as game developers must ensure that the persistent data is consistent (a unique object may exist in one and only one place); that the game solution (as a service) is efficient in that it minimizes the overhead consumed by the persistence features; and finally that the solution is scalable across thousands of new users being added and increased levels of activity (Zhang, Kemme, & Denault, 2008). In persistent play as players spend more time, utility increases as a function of time in the game.

1.3.5 Genre & Type of Play

The game's genre and its play type are inextricably linked. Game review websites and magazines frequently use these terms interchangeably leading to great confusion. Indeed, it has been observed that with the gamers and the game publishers and developers, the word "genre" is usually referring to the type of user experience delivered (Ye Z. , 2004) and may focus on visual style and conventions followed by interface metaphor, pace, and control scheme as shown in Table 1. Genre has been used to describe play type in the academic literature as well (Achterbosch, Pierce, & Simmons, 2008). It has also been observed that the concept of play type as shown in Table 2 and genre must be explicitly defined as there is no consensus about even a relatively simple concept as a FPS (First Person Shooter) game (Nieborg, 2004). Within the industry, RPG (Role Playing Games) and their massively multiplayer online varieties (MMORPGs) are occasionally described as being a separate genre further complicating matters.

Table 1.1 – Common genres

Genre	Examples
Action	Dead Space
Adventure	World of Warcraft
Fighting	Mortal Kombat
Simulation	SimCity, Need for Speed
Puzzle	Break Out
Sports	Virtual Pool
Music/Dance	Guitar Hero

Play type may be one of several different types of game mechanics or may be a combination of several. That said, all data-driven games share a common set of architectural conventions (White, Demers, Koch, Gehrke, & Rajagopalan, 2007).

Table 1.2 – Types of game play

Play Type	Examples
Real Time Strategy (RTS)	Travian
Turn Based Strategy (TBS)	Civ4
First Person Shooter/Sneaker (FPS)	America's Army
Role Playing Game (RPG)	World of Warcraft
Social Game	Farmville
Flight (including Space Flight)	EvE Online
Exercise/Fitness	Wii Fit

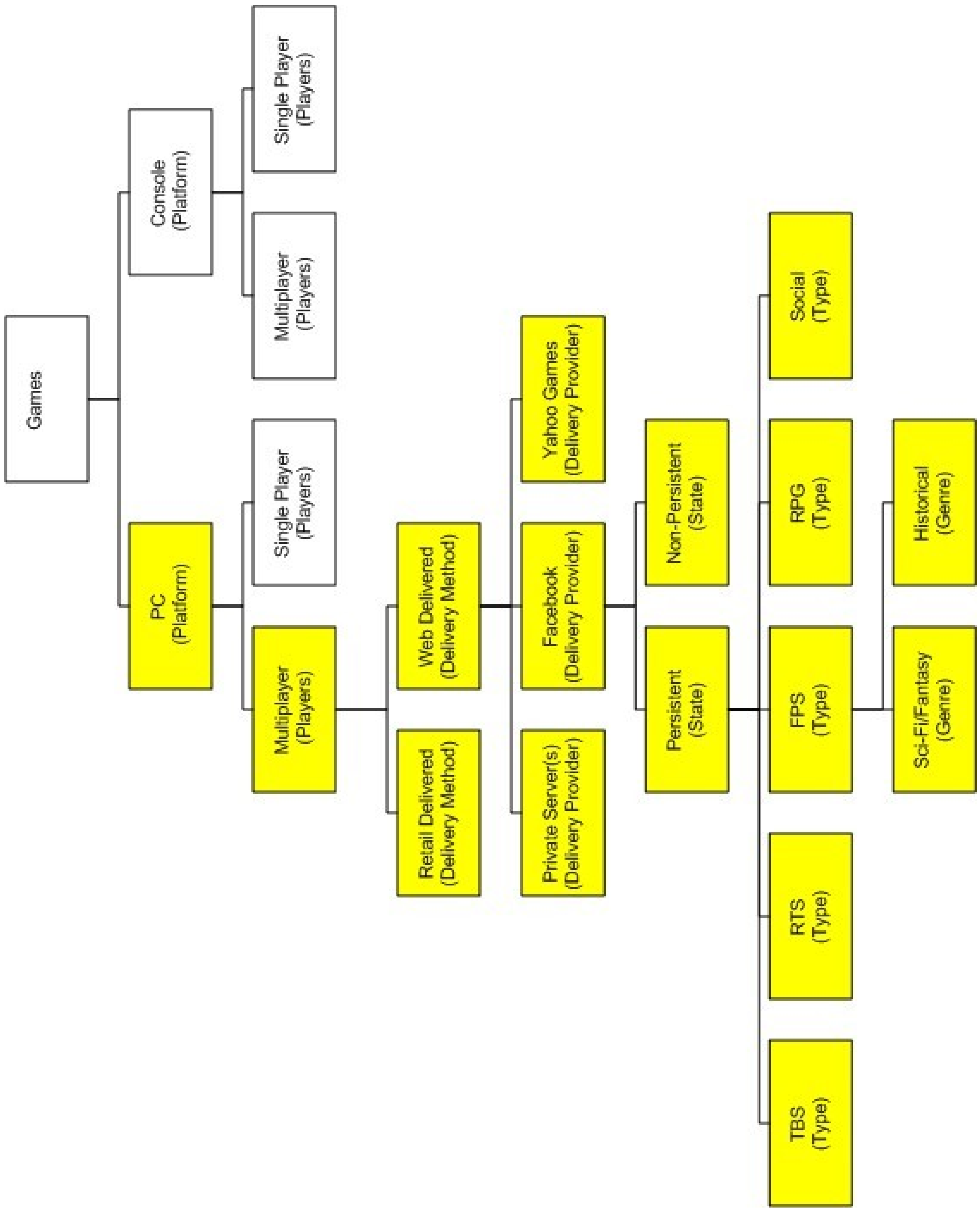

Figure 1.1: Game classification scheme

1.4 Pricing of Online Games

Online games are digital experience goods. Traditional experience goods such as a vacation or viewing a movie are competitors for online games. Online games purchases are generally considered to be entertainment expenditure within a household. This expenditure of a gamer on a particular game is usually dependent on the number of players in the game, the level of development investment in creating the game, and the quality of service in providing access to the game.

1.4.1 Industry Structure

The online game industry is constituted of a collection of members, each providing a different service that, when combined, eventually results in the game being delivered to the consumer. This service supply chain is complex and dynamic with members continuously entering and exiting their market space. A generally accepted model is that game developers produce the code upon which the game engine operates while publishers (just as in other industries) provide marketing and distribution solutions to get the game to consumers and set the final retail price. However, several other entities such as hosting providers or application service providers must get involved when a game is an online multiplayer game.

1.4.2 Experience Goods

Games (and other forms of Digital Interactive Entertainment) are an *experience good* and as such the value of a game can only be determined *post hoc* by the consumer (Choi & Kim, 2004). More so, games have been described as a *designed experience* where players' understanding and identity are developed through cycles of performance within the virtual environment (Squire, 2006). MMO games generally fit the four characteristics of a service as they are: *intangible* in that a player may purchase the right to play the game but not any form of ownership; *inseparable* as a player cannot enjoy a MMO game without consuming it (experiencing it); *variable* in that there is a constantly changing dynamic between players, the developers, and the virtual world; and *perishable* in the case of subscription-based models in that the "eligible game time" ends after some agreed-upon period regardless of whether or not the account has been accessed (Zackariasson & Wilson, 2004). With respect to dynamic pricing of experience goods in general, research has shown that in a mass market, prices decline as time passes; however, in a niche market, prices start low and move upwards with respect to time (Bergemann & Valimaki, 2006). Alternatively, it may be in the interest for the provider to initially offer a high value product and then slowly (or perhaps suddenly) switch to offering low value products in a (likely) successful effort to exploit a good reputation for quality (Gale & Rosenthal, 1994). For at least some experience goods, research efforts indicate that mixed pricing methods may result in greater values for profit maximization (Bhattacharjee, Gopal, Lertwachara, & Marsden, 2003).

Pricing experience goods properly can be difficult for many corporations. However, environments where individuals congregate have traditionally been recognized by marketers as being an effective place for advertising. Virtual environments are frequently highly interactive, collaborative, and increasingly commercial. Within the virtual environment SecondLife, companies such as Adidas, BMW, IBM, Reuters, and Sears among others maintain some form of virtual presence; further, organizations such as NASA and Harvard Law also maintain a virtual presence (Barnes, 2007). Software development can be a risky business proposition as many projects fail to be completed or are otherwise deemed unviable, thus developers and publishers have traditionally followed "tried and trusted approaches" which have some history of success (Charles, et al., 2005). Commercial success is not guaranteed; however, typically a sequel to a popular game or an expansion to an already successful game does mitigate some of the risk of the investment.

Producers of experience goods may follow a monopolistic pricing policy. While the monopoly may be weak as it is derived from product differentiation, and other firms may be able to somewhat influence the pricing decision (Shapiro C. , 1983), the firm can be seen to act as a monopolist. Also, a firm may need to build a reputation in order to price higher than it otherwise could, or it may be able to "milk" its already established reputation; both of which scenarios render network effects more critical. With monopolistic pricing, producers of experience goods will automatically set the price high and will maintain high quality (Liebeskind & Rumelt, 1989). This tendency towards quality originates from the fact that, as games are discretionary entertainment expenditures, an individual does not need to purchase one. A consumer will purchase a game that they consider to be a good value. That said, as firms decrease in size relative to the size of the total market for experience goods, the equilibrium product quality increases as the market moves towards full information equilibrium (Riordan, 1986) meaning that customers tend to be better informed about the quality of a company's offerings under these conditions. With imperfectly informed consumers, there is a risk of market failure partially induced by the moral hazard arising from the observation that sales volume (at least initially) is independent of product quality (von Ungern-Sternberg & von Weizacker, 1985). Typically a dishonest approach is discovered by the market and is not a long term issue, particularly in the area of subscription based revenue generation as network effects work quickly to spread information about inadequate products throughout the market. Each game provider is a monopolist who charges a price based on several factors.

1.4.3 Factors of Pricing

Many attributes contribute to the value and correspondingly to the price of an online multiplayer game; however, we choose to focus our attention on community size, development investment, and quality of service. The first ensures that the game is indeed multiplayer, the second permits sufficient depth to the game, and the latter allows the game to be both "playable" and "online."

1.4.3.1 Player Base & Community Size

While there is a considerable amount of literature that examines services and experience goods with respect to pricing, multiplayer games are a particularly special case and one which has been neglected to date in the literature. Network externalities play a considerable role in the demand of MMO games. Without a large player base, a game feels "empty." Interestingly, both positive and negative network externalities exist. Positive network externalities exist based on the quality and quantity of opponents whereas negative network externalities typically stem from technical issues and reputation problems (Meagher & Teo, 2005). Because MMO games frequently have a large following and a large community, negative feedback such as complaints and criticisms can diffuse as fast as positive feedback. In both cases network externalities make the total effect much larger than would normally be the case in a different business environment. Generally, it is difficult to overcome the many obstacles that growth in popularity brings, and many companies fail (Irwin, 2008). One measure of network externalities is the presence of fan sites. These sites are useful for user research as they influence the evolution of the game's community (Johnson & Toiskallio, 2005). Some fan sites have developer or publisher support and as such are "official" despite being managed by third parties. Further evidence of network externalities are growth in publications by or about the digital entertainment industry (Ye & Xu, 2003). With large social networking sites opening their systems to developers, applications are able to spread in a "viral" manner and may experience exponential growth (Nazir, Raza, & Chuah, 2008) which in turn leads to even higher traffic on the social networking site. Other network externality drivers are professional reviews. The effects of critical reviews are frequently difficult to accurately measure and the relationships derived may be spurious (Reinstein & Snyder, 2005), however at least in the case of some experience goods such as movies, a large positive effect on revenue exists when positive reviews come from a professional possibly due to the reviewer's access to a broader network than is normally the case.

Games have a difficult time surviving unless new players are regularly introduced into the environment (Steinkuehler, 2006) to mitigate the attrition rate of established players; however, this entry of new players may lead to conflict with established players and to negative implications for the game environment as new players are typically not capable of sustained competition with more experienced players. To complicate matters, certain games have steeper learning curves than others for even basic tasks and thereby suffer usability issues which can be overwhelming to new users and cause a lack of new player retention (Cornett, 2004). Sufficient expenditures in certain areas of development investment can mitigate these concerns.

1.4.3.2 Development Investment

On the supply side, MMO game providers have to concern themselves with the game design and delivery. Few companies have both as a core competency (Shaikh, Sahu, Rosu, Shea, & Saha, 2004). Game architecture, playability and game inconsistencies, and fairness are concerns for game providers (Brun, Safaei, & Boustead, 2006) and correction of such issues detracts for a provider's bottom line. Game production is a complicated business in an extremely dynamic environment involving numerous entities striving to deliver value to the end users (Johns, 2006). Of particular import to those who study games and gaming is the observation that the industry is cyclical but operates almost completely independent of the larger economy's cycles with substantial first mover advantages being present (Crandall & Sidak, 2006).

MMO games are experience goods in that a player must interact with the product in some definite way over some period of time in order to gather information about the actual product, its more intricate features, its quality, and its value with respect to price. Players typically concern themselves with features such as quality of graphics, elaborateness of game mechanisms such as combat or economics engines, as well as with the smoothness or completeness of the gaming experience. All of these items are a direct function of the amount invested during the development phase. While some aspects can be determined by the customer via the search for a particular product (i.e. a new online game) such as a partial feature list, until the player is actively involved in the game for some time, final judgment as to whether or not it will be played over a longer time frame must be postponed. This is because the seller of the experience good has (due to the nature of the product) bundled most of the information about the product within the product itself (Shapiro C. , 1983). While it has been assumed in most economic literature that customers can immediately tell the quality of the experience good upon initial consumption, we are of the opinion that due to the complexity of the features of MMO games, the fact that players who are new to a MMO game are not (typically) given access to upper-level resources or benefits that more advanced players have, and the size and scope of the virtual worlds, that the customer forms an initial opinion which evolves as they interact with the game. Generally, the game contains mechanisms or documentation where customers are aware of the existence of items which they have not yet earned access to. Players are able to improve their in-game persona or existence with the intention of being able to use or earn these better items. With increased investment in the form of game development, the customer will take a longer period of time to form a final opinion about continued play of the game. Sufficient expenditures in terms of publishing or promoting costs for the game will ensure that players have a sufficient amount of information to make a decision about the correct value of the game.

1.4.3.3 Quality of Service

The Quality of Service and the quality of the actual game are two different factors. The former is a function of the development investment. The latter is a function of the amount expended monthly to provide adequate bandwidth, customer service, and other such expenses. Online gamers are particularly sensitive to Quality of Service (QoS) issues (Zander & Armitage, 2004). As an experience good, players (new and continuing players) make the decision to purchase access to an MMO (or other experience good of similar characteristics) as a result of an internal calculation based on pre-choice expectations; information sources such as advertising, critical reviews, and word of mouth; and latent product interest which in turn influences post choice decisions such as whether or not to "spread the word" or otherwise recommend the experience to others (Neelamegham & Jain, 1999). As an exceptionally powerful component of demand for a product or service, this word of mouth interaction has particularly important implications for the positive network externalities discussed in later sections. Since quality (and value) is determined *post hoc*, players may find that firms compete aggressively for them to try their game for some initial period (Villas-Boas, 2006). Interestingly, firms which command a large market share are able to price significantly higher as these firms are able to take advantage of a relatively larger population of consumers who experience a better "fit" with the product. Companies generally concern themselves with ensuring that networks are stable with sufficient bandwidth, that there is sufficient server space for game play, and that customer service is adequate given the game's community and the requirements of said community. Return policies are a difficult subject with experience goods as players may form post-purchase regrets for a variety of reasons (Chee, 1996), some of which may be induced by switching costs. Given that some games allow players to engage in game play prior to have an outlay of funds, it is possible to view the trial period as a variation of the "return policy."

1.5 Common Streams of Revenue & Pricing Approaches

Building a sustainable revenue model has proved to be challenging for a number of online gaming companies (MacInnes & Hu, 2007) as many game developers and publishers are forced to direct their efforts towards technical and game-environment issues. Media reports that perhaps as many as thirty-three revenue schemes may exist (Perry, 2008), and as a result, numerous pricing related research efforts exist. Two-part pricing models (those models with both a fixed as well as a usage-based cost to consumer) have been applied to online games due to the presence of strong network externalities and the useful life-span of the game as a function of the rate of creative destruction (Meagher & Teo, 2005). Efforts have been made to map business models in MMO games (Alves & Roque, 2005). Other efforts have presented MMO game business models as being one of two options: as a portal which allows access to games, or on subscriptions permitting presence in the virtual environment (Sharp & Rowe, 2006).

Information goods and pricing of such have been topics of interest within the research community for several years. In cases where there are two firms providing a similar service, two different pricing schemes have been studied. In terms of subscription pricing versus pay-per-use, there are stable equilibrium in a few special cases; however, direct competition on the basis of price will usually prove destructive to all parties involved (Fishburn & Odlyzko, 1999). A selection of current MMO offerings from different game providers is listed in Table 3. There are five basic pricing models: Fixed Purchase Price, Fixed Purchase Price plus Subscription, Subscription, Limited Free Play, and Free Play.

Table 1.3 – Current MMO games

Game	Pricing	Subscribers (in 000's)
World of Warcraft (Activision Blizzard)	$39.99 Installation/Expansion $14.99 Monthly Subscription* $13.99 Three Month Subscription* $12.99 Six Month Subscription*	> 11,500 (Blizzard, 2008)
EVE Online (CCP)	Free Installation Free Seven Day Trial Subscription $14.95 Monthly Subscription* $12.95 Three Month Subscription* $11.95 Six Month Subscription* $10.95 Twelve Month Subscription*	> 300 (Cohen, 2009)
Runescape (Jagex Games)	Free Limited Play $7.50 Monthly Subscription* $6.495 Two Month Subscription* $5.997 Three Month Subscription* $5.831 Six Month Subscription* $5.583 Twelve Month Subscription*	> 200,000 (Saltzman, 2012)
Pirates of The Burning Sea (Flying Lab)	Free Limited Play	> 15 (Flying Lab, 2012)
Farmville (Zynga)	Free Limited Play	> 10,000 (WSJ, 2009)
Evony (Evony)	Free Limited Play	> 10,000 (Evony, 2010)
Guild Wars (NC Soft)	Single Purchase	> 6,500 (Joystiq, 2010)
Battlefield Heroes (EA)	Free Limited Play	> 1,500 (Kotaku, 2009)
	* indicates a per-month price	

1.5.1 Single (Per Unit) Purchase Price

The first model requires players to purchase the game (either at a retailer or online) and then requires no additional fees from the consumer. While such pricing is not typically representative of MMO games, examples of this strategy do exist (Arena Net, 2010). Guild Wars, developed by Arena Net and published by NC Soft, allows customers to download the game client for a fee or purchase the client at a different retailer without the financial burden of subscription fees. Other examples of subscription free multi-player support include Age of Empires III (Ensemble Studios, 2010) where a free Ensemble Studios Online account is included with the initial purchase of the game, and StarCraft by Blizzard Entertainment (Blizzard Entertainment, 2010) where a

Battle.net account is included with initial purchase. MMOs and specifically Blizzard Entertainment's success in the multiplayer StarCraft platform has been studied with respect to how it has changed or shaped changes in cultures (Huhh, 2008).

1.5.2 Subscription

The second model does not require the purchase of the game software, but it does require players to purchase a subscription to play the game. Users have full access to all of the game features upon subscription to the game service, typically following the expiration of some form of a free or complimentary trial period offering. For example, CCP's client for its MMO offering, EVE Online, is available for download for free from the game's web portal and has been intentionally seeded by CCP into BitTorrent.

1.5.3 Single Purchase Price Plus Subscription

The third model requires players to purchase the game (either at a retailer or online) and then purchase a monthly subscription. Users under this pricing model have full access to the features available from the publisher for the duration of their subscription. Usually, the initial purchase of the game includes a short (i.e. 30 days) free subscription period upon completion of which, the user must begin paying for access to the game and its features. The largest online game in terms of market share, World of Warcraft (Blizzard Entertainment, 2010), uses such a model. World of Warcraft has been studied as a means of examining characteristics of MMOs that appeal to consumers (Ducheneaut, Yee, Nickell, & Moore, 2006).

1.5.4 Limited vs. Fully Free Play

The fourth model, limited free play or fully free play, may come in a variety of forms. Users are faced with a set of restrictions. These may be restrictions in terms of Character Classes or Subclasses in the case of RPGs, Weapons or Items in the case of FPS games, Premium/Unique Items in the case of Social Games or RTS games, or Map Access in any of the above. Presence of advertising may also be considered a restriction.

Players have these restrictions removed by either subscribing to the game service, or by engaging in microtransactions. Microtransactions (Snider, 2010) are the purchase of in-game credits for the goal of exchanging such credits for rare or useful items or the direct purchase of said items. In effect, some percentage of the development investment is given away while a fee is charged to the players for access to the remainder. With some games (i.e. Travian, Sims, Battlefield Heroes, Lineage) players convert real currency into virtual currency (or game credits) with which useful items can be purchased within the game. Bringing real money into a virtual environment can be controversial at best. Different groups of players, all with different motivations for playing the game, view the infusion of real currency differently. Some view this action (legal or otherwise) as cheating while others view it much more favorably (Lehdonvirta V. , 2005). Further, experiments have been conducted by corporations where a fee is charged for a small set of changes to a player's account as has been the case with most of the games delivered by Facebook as well as games such as Ultima Online, a MMORPG by Electronic Arts.

In some games, advertising is presented to players. Occasionally, such advertising is presented to both paying and non-paying players; however, it may be presented only to non-paying players. Advertising comes in a variety of forms (Faber, Lee, & Nan, 2004) and may include pop-up ads, sponsorships, ads embedded in the game environment, banner ads, pull down menu banner ads, affiliated commercial sites, and so on. Indeed, ad revenue is critical to certain games' sustainability to the degree that these games are called Advergames (Faber, Lee, & Nan, 2004). Embedded (in-game) advertising has grown in popularity among markets such that there are corporations who now specialize exclusively in ad placement (dynamic and otherwise) for games. While it has been proposed that four types of advergames exist, it is interesting to note that this phenomenon has now developed to the point that some games have been designed wholly or at least to some degree to deliver a message to a player to change a real world behavior (Svahn, 2005). Within game environments, due perhaps to the highly immersive nature of the games, players may have difficulty recalling embedded billboards and as such have a lower than anticipated effect on a player's willingness or tendency to modify real-world behavior (Chaney, Lin, & Chaney, 2004); however, higher (more sophisticated) levels of ad integration into the game (environment and mechanics) is generally met with higher levels of recall for brands which the gamer is already aware of (Winkler & Buckner, 2006). Where advertising enhances the realism of the game environment, many players have been found to actually welcome the presence of such ads (Nelson, Keum, & Yaros, 2004). Not all gamers support advertising with the game environment as is illustrated by the virtual terrorist organization self dubbed the Second Life Liberation Army and its actions against advertisers (Steiner, 2008).

There are a large number of free online games and services scattered across the Internet (Anderson, 2008). The final model, fully free play, involves the removal of all restrictions on items, map access, characters, etc. and enables users to fully explore the game's features. Such free play does not expire (i.e. not a Trial), relying instead on donations, advertising, and the purchase of "non-essential customizations" such as specialized clothing or skins.

1.6 Conclusion

Over the previous sections, we have outlined a brief history of games and gaming. We have developed a list of critical distinctions between game types into a classification of games. Discussions in previous sections allowed us to identify important factors in the valuation of certain types of games and to examine how companies can earn revenue from such games. The objective of this dissertation is to examine two of these pricing models for multiplayer non-persistent games in greater detail. The first model is the Single Purchase Model and assumes that an individual buys a game once and no longer must pay any additional sum to continue using the game. The second model is the Subscription model wherein the player must make a periodic decision as to whether or not to continue playing the game. Both models are examined analytically, through use of numerical examples, and in a simulation environment.

CHAPTER 2: PRICING MODELS FOR ONLINE MULTIPLAYER GAMES

2.1 Model 1: Single Purchase Model

In the first model, players pay a one-time price for the game, but do not incur any additional fees that take the form of subscription. We assume that these players, upon paying the purchase price, do not incur any additional costs in the form of buying additional features or other perks, or that such items or "boosts" or "buffs" are not available. In this model, the game provider can choose to change the price of the game at the beginning of any period.

Within this model the players receive a certain amount of satisfaction or utility from the game. Due to network externalities, the number of active players is of concern for individuals looking to receive some amount of utility from the game. Quantity sold directly influences the amount of active players. Users receive satisfaction from a variety of sources within the game; however, the two most pertinent to MMO game play are the amount of features or depth of the game and the number of active players. Games which lack depth are less likely to attract or retain a large player base as they are too mundane or do not give players sufficient room to explore. Development costs in the form of innovative features and extensive content regularly draw and keep players which in turn cause an upward spiral in demand as the player base size increases. Finally, players are sensitive to quality of service issues and as such, QoS (or the absence of QoS issues) represented by the company's expenditures in providing a certain level of customer service have a direct impact on the utility of a player in the game. Use of a Cobb Douglas Utility Function permits the capture of a variety of factors and their relative influence on utility. While this type of function was originally developed for describing the relationships between different factors of production, its numerous extensions include use to describe relationships of various factors and their effects on utility (Mas-Colell, Whinston, & Green, 1995).

The utility for an online multiplayer game comes from its player base, the amount of content and its completeness, the level of service provided, and the degree to which a game is marketed to potential players. In this model, we assume publishing effort as an exogenous constant and capture the interest of the player base in the game in period t via the number of players in the game in period $t-1$, (n_{t-1}). This parameter is of particular import as network effects are considered key drivers of demand for products that exhibit strong network externalities, especially multiplayer games. The importance of network externalities is captured by y in this model. Content and service level are captured by the development cost and the service cost $\left(C_D, C_{S_t}\right)$ respectively. Table 2.1 contains the notation used throughout this model. The mean utility a purchaser gets from a multiplayer online game in period t is best represented as:

$$u_t = f\left(n_{t-1}, C_D, C_{S_t}\right) \qquad [1.1]$$

Table 2.1 – Notation used

Symbol	Description
$\boldsymbol{P_t}$	Purchase Price in period t
$\boldsymbol{C_D}$	Cost of Development (fixed cost incurred by the game developer)
$\boldsymbol{C_{P_t}}$	Cost of Publishing (fixed cost incurred by the game publisher) in period t
$\boldsymbol{C_{S_t}}$	Cost of Service (variable cost incurred by the game provider) in period t
$\boldsymbol{Q_t}$	Quantity of Games Sold in period t
$\boldsymbol{U_t}$	Utility of Game (as seen by the player) if purchased in period t
$\boldsymbol{n_t}$	Number of Active Players in period t
$\boldsymbol{N}$	Size of Market Segment for Game Type/Genre combination
$\boldsymbol{\varphi}$	Discount Rate
$\boldsymbol{\alpha, \beta, y}$	Relative effects of C_D , C_S, and n_t on Market Segment N
$\boldsymbol{\delta}$	Retention Rate
$\boldsymbol{\lambda}$	Pre-release market perception
$\boldsymbol{\mu}$	Growth Factor
$\boldsymbol{g}$	Beta Group Size
$\boldsymbol{n_0}$	Initial period network effects ($g * \lambda$)

A particular specification of the above function is a variation of the Cobb Douglas utility function:

$$\Gamma_t = kC_D^{\alpha}C_{S_t}^{\beta}n_{t-1}^{y} \qquad [1.2]$$

Where, $\alpha \in [0,1)$, $\beta \in [0,1)$, and $y \in [0,1)$, are parameters of a particular game and k is a constant. Figure 2.1 shows the mean utility where $\beta = 0$.

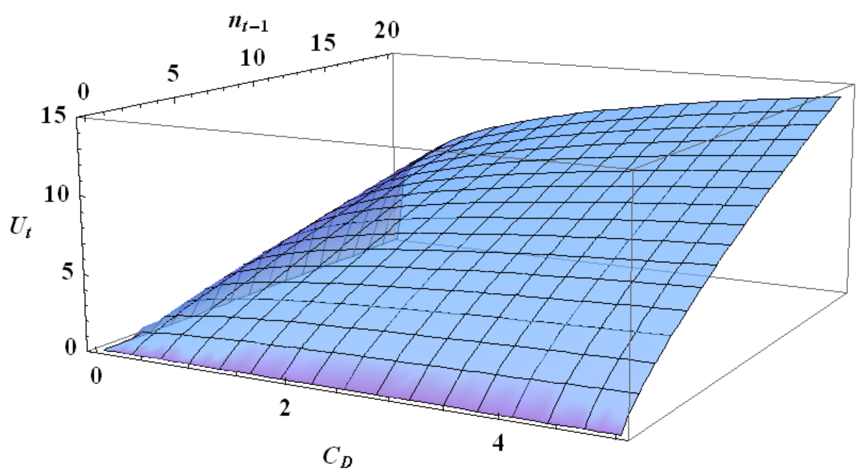

Figure 1.1: Utility function

We assume there is a nonnegative discount rate of φ for both the future consumer utility and future revenue and define:

$$\theta_i = \frac{1}{(1+\varphi)^i} \qquad [1.3]$$

The total utility that a player obtains by buying the game in period *t* and playing until *T* is:

$$U_t = \sum_{i=0}^{T-t} (\mu^i \Gamma_t \theta_i) \qquad [1.4]$$

Where $\mu \in (0, \infty]$, represents the customers' expectations of the game's growth factor. The customers' expectation of growth is a complex factor that is a function of several components including the topic or theme of the game and the popularity of this theme. This may be indicated by the presence of movies or TV shows that have a shared theme. Customers may expect the game to become popular or not due to the genera of the game, the publisher's reputation, as well as the presence of other media. We use a discounted utility function since players who purchase a product early will enjoy it longer and will have more utility from the product. This utility function captures the utility gained by a player in the period of purchase and of all future periods of use. For an individual player, their utility is assumed to be uniformly distributed with mean of U_t and a range of $2bU_t$ where $0 \leq b \leq 1$ on:

$$[U_t(1-b), U_t(1+b)] \qquad [1.5]$$

Players enter the game periodically and remain for some duration of time. New entrants are captured via the quantity sold (Q_t) while players who exit the game are represented by L_t. Of importance is the notion of an active player base. A game where the player base is small has less value as there are few opportunities for player-to-player interactions (whether in the form of team questing, PvP, or simply chatting). No upper limit to the active player base size is assumed as MMO games are typically scalable by design. The size of the active player base at time period t (n_t) is determined in part by the quantity of the game sold, the effectiveness of the game provider, and time. Poor (or simply ineffective) customer service results in players leaving the game. Other issues faced by the provider include the accessibility of the gaming experience. As noted earlier, gamers may be intolerant with respect to connection quality. Finally, games (like all products) follow some form of a life cycle. In the moment in which the servers go "live" for the first time the life cycle begins. While a game may continue indefinitely, we assume that a game "dies" when the company no longer feels that it is viable to continue providing service or support to existing customers and ceases efforts to acquire new or additional customers, or when n has reached a minimum at which point the game is no longer playable. Since the game may be abandoned by either party at any point, we assume that both parties are equally able and willing to exit the playing environment. Players may choose to leave or exit a game for a variety of reasons. Players may choose to leave due to 1) poor service level, 2) interactability issues, or 3) "Real Life" issues. Reductions in the player base due to service level changes may stem from connectivity issues or from issues related to poor customer service or an inadequate C_S expenditure. Interactability losses can be attributed to a player "completing" the game, a player getting "bored" with the game, or a player getting "stuck" in the game all of which depends on C_D in the form of features and content, documentation, and community tools. The last of the three reasons that players leave a game, real life issues, cannot be influenced by the profit seeking entities and so is not considered. The active player base of the game at any given time period (n_t) is:

$$n_t = \delta n_{t-1} + Q_t \quad [1.6]$$

Where δ is the mean retention rate, $0 < \delta \leq 1$. We assume δ is a game parameter that is exogenous and is unique to each game offered. To simplify the analysis, we assume C_S and C_D are given and thus we treat δ as a constant to allow us to focus on the pricing aspects of this model. Players choose to enter the game if:

$$U_t > P_t \quad [1.7]$$

Assuming that players only purchase the game once, the quantity sold in period t:

$$Q_t = N_t \int_{P_t}^{U_t(1+b)} \frac{1}{2bU_t} dx = N_t \frac{U_t(1+b) - P_t}{2bU_t} \quad [1.8]$$

Substituting for $\mathrm{N_t}$ and integrating yields:

$$Q_t = \left(N - \sum_{i=0}^{t-1} (Q_i) \right) \frac{U_t(1+b) - P_t}{2bU_t} \quad [1.9]$$

The game publisher maximizes expected profit in problem SP1:

$$\max: Z = \sum_{t=1}^{T} \left(Q_t P_t - C_{P_t} - C_{S_t} \right) - C_D \quad [1.10]$$

We assume that the beta testers must purchase a copy prior to playing the game post beta period:

$$\sum_{t=1}^{T} Q_t \leq N \quad [1.11]$$

Additionally, the non-negativity constraints:

$$Q_t \geq 0, t = 1,2, \ldots T \quad [1.12]$$

and

$$P_t \geq 0, t = 1,2, \ldots T \quad [1.13]$$

2.1.1 Solution for Three Period Model

For three time periods, closed form solutions to the first order conditions for P_2 and P_3 exist so that Z is a function of P_1. This means that a 1-dimensional search can be used to find the optimal P_1. We can show that the solutions satisfy the sufficient conditions for optimality for Proposition 1 in Proof 1. We use three time periods for a product life cycle where we have three pricing levels: price at *introduction*, *maturity*, and *decline*. Also, we hold $C_{S_t} = C_S$ and $C_{P_t} = C_P$ as exogenous. In the first period $(t = 1)$, we assume that $n_0 = g * \lambda$ and $y = 1$. To simplify, let:

$$A = kC_D^{\alpha} C_S^{\beta} \qquad [1.14]$$

$$\Gamma_t = An_{t-1} \qquad [1.15]$$

2.1.1.1 Proposition 1

For g sufficiently small, if $\big(17N + g(-17 + 24\delta)\big) > 0$, then the following solution to problem SP1:

$$P_3^* = \frac{N_A^2 P_1^2 (15\delta - 7) + 6AgN_A P_1 N_B (31\delta - 8)\lambda + 576A^2 g^2 N_B^2 \delta \lambda^2}{3g\lambda(7N_A P_1 + 48AgN_B\lambda)} \qquad [1.16]$$

$$P_2^* = \frac{N_A^2 P_1^2 (7 + \delta) + 6AgN_A P_1 N_B (15 + 2\delta)\lambda + 36A^2 g^2 N_A^2 (8 + \delta)\lambda^2}{3g\lambda(7N_A P_1 + 48AgN_B\lambda)} \qquad [1.17]$$

And

$$\frac{\partial Z}{\partial P_1} = -N_A \frac{\begin{gathered} 7N_A^3 P_1^3 (\delta_B)^2 + 6gN_A^2 P_1^2 \big(-392P_1 + AN_B(\delta_B)(140 + 19\delta)\big)\lambda + \\ 144Ag^2 N_A P_1 \left(4AN_A^{2^2}(\delta_B)(8 + \delta) - 7P_1\big(39N + g(32\delta - 39)\big)\right)\lambda^2 + \\ 834A^2 g^3 N_B \left(AN_A^2 - 16P_1\big(15N + g(8\delta - 15)\big)\right)\lambda^3 + 331776A^3 g^4 N_A^2 \lambda^4 \end{gathered}}{144Ag^2\lambda^2(7N_A P_1 + 48AgN_B\lambda)^2} = 0 \qquad [1.18]$$

Satisfies the necessary optimality conditions. Where to simplify:

$$N_A = g - N \quad [1.19]$$

$$\delta_A = \delta - 1 \quad [1.20]$$

$$N_B = N + g\delta_A \quad [1.21]$$

$$\delta_B = 7 + \delta \quad [1.22]$$

2.1.1.2 Proof 1

Solving:

$$\frac{\partial Z}{\partial P_3} = 0 \quad [1.23]$$

Yields

$$P_3 = \frac{2N_A^2 P_1^2 \delta_A + 3gN_A P_1\big(P_2 + 4AN_B(2\delta - 1)\big)\lambda + 73A^2g^2N_B^2\delta\lambda^2}{12g\lambda(N_A P_1 + 6AgN_B\lambda)} \quad [1.24]$$

Substituting P_3^* into Z and solving:

$$\frac{\partial Z}{\partial P_2} = 0 \quad [1.25]$$

Yields Equation 1.17 as well as Equation 1.16 after some substitution. Substituting back into Z and computing $\frac{\partial Z}{\partial P_1}$ yields Equation 1.18. To examine the concavity of Z in P_1 we compute:

$$\frac{\partial^2 Z}{\partial P_1^2} = \frac{N_A\begin{pmatrix} -49N_A^4P_1^3\delta_B^2 - 336gN_A^3P_1^2(-49P_1 + 3AN_B\delta_B^2)\lambda - \\ 6912Ag^2(g-N)^2P_1N_B(-49P_1 + AN_B\delta_B^2)\lambda^2 - \\ 1728A^2g^3N_AN_B^2\big(-1344P_1 + AN_B(8+\delta)(56+9\delta)\big)\lambda^3 + 5308416A^3g^4N_B^3\lambda^4 \end{pmatrix}}{144Ag^2\lambda^2(7N_AP_1 + 48AgN_B\lambda)^3} \quad [1.26]$$

Equation 1.25 is discontinuous at:

$$-\frac{48AgN_B\lambda}{7N_A} \quad [1.27]$$

The limit of X where X is the numerator of Equation 1.25 is

$$\lim_{g\to 0}(X) = 49N^5P_1^3(7+\delta)^2 > 0 \quad [1.28]$$

Thus the sign is determined by the sign of the denominator. Solving the following for P_1

$$144Ag^2\lambda^2(7N_AP_1 + 48AgN_B\lambda)^3 = 0 \quad [1.29]$$

Yields:

$$P_{1c} = -\frac{48Ag\big(N + g(-1+\delta)\big)\lambda}{7(g-N)} \quad [1.30]$$

The game publisher will not set a price beyond the maximum utility $2A\lambda g$ so we observe that subtracting the maximum utility from Equation 1.29 yields:

$$-\frac{2Ag\big(17N + g(-17+24\delta)\big)\lambda}{7(g-N)} \quad [1.31]$$

If $(17N + g(-17+24\delta)) > 0$ then P_{1c} is greater than the maximum utility and Z is concave on $[0, 2A\lambda g]$ and the proof is complete.

2.1.2 Numerical Example

With the following parameters, we find a solution for the single purchase model where $T = 3$.

Table 2.3.1 – Single purchase model numerical example

Symbol	Value	Definition
$\boldsymbol{\alpha}$	0.5	Relative Importance of C_D
$\boldsymbol{\beta}$	0.5	Relative Importance of C_P
$\boldsymbol{y}$	1	Relative Importance of Q_{t-1}
$\boldsymbol{N}$	5,000,000	Population Size
$\boldsymbol{Q_0}$	n_0	Quantity Sold During Beta
$\boldsymbol{g}$	15,000	Number of Beta Testers
$\boldsymbol{C_D}$	600,000	Development Cost
$\boldsymbol{C_P}$	50,000	Publishing Cost
$\boldsymbol{C_S}$	100,000	Service Cost
$\boldsymbol{\lambda}$	50	Pre-release market perception
$\boldsymbol{\mu}$	1	Customers' Expectation of Growth
$\boldsymbol{\delta}$	0.5	Retention Rate During Period
$\boldsymbol{\varphi}$	0.0	Discount Rate
$\boldsymbol{b}$	2	Spread of Uniform Distribution
$\boldsymbol{k}$	0.00000000001	Scaling Constant

The following solution reflects the optimal values for the decision variables P_t as Z is maximized:

Table 2.3.2 – Optimal prices

Decision Variable	Value
P_1	5.876
P_2	12.064
P_3	5.936
Z	31,940,898.000

The values for certain important variables for each period are shown in Table 2.3.3.

Table 2.3.3 – Period values

Variable	Value	Variable	Value
U_1	5.511	n_1	2,334,885.0
U_2	11.439	n_2	2,423,544.0
U_3	5.936	n_3	1,912,529.0
Z_1	13,526,761.0	Q_1	2,327,385.0
Z_2	15,004,132.0	Q_2	1,256,102.0
Z_3	4,010,005.0	Q_3	700,757.0
		$\sum Q_t$	4,284,243.0

2.2 Model 2: Subscription

The following model assumes that players obtain the game without a one-time purchase cost but incurs periodic subscription fee, F_t to play. Some changes in notation are necessary and are reflected in Table 2.4.

Table 2.4 – Symbols used

Symbol	Description
$\boldsymbol{F_t}$	Subscription Fee in period t
$\boldsymbol{u_t}$	Utility of Game as seen by a player in period t
$\boldsymbol{n_t}$	Quantity of Game Subscriptions sold in period t

We use the same variation of the Cobb Douglas utility function as in the Single Purchase model on the same distribution, where:

$$u_t = kC_D^{\alpha}C_{S_t}^{\beta}n_{t-1}^{y} \qquad [2.1]$$

Where, $\alpha \geq \in [0,1), \beta \in [0,1)$, and $y \in [0,1)$, are parameters of a particular game. A player chooses to pay the subscription fee if:

$$u_t > F_t \qquad [2.2]$$

Since players subscribe for one period at time t, there are N potential players in the market at the beginning of each period. The number of game subscriptions purchased during period t is:

$$n_t = N \int_{F_t}^{u_t(1+b)} \frac{1}{2bu_t} dx = N \frac{u_t(1+b) - F_t}{2bu_t} \qquad [2.3]$$

Which gives:

$$n_t = N \frac{C_D^{\alpha}C_{S_t}^{\beta}n_{t-1}^{y}(1+b) - F_t}{2bC_D^{\alpha}C_{S_t}^{\beta}n_{t-1}^{y}} \qquad [2.4]$$

The firm maximizes the expected profit given by problem SM1:

$$\max: Z = \sum_{t=1}^{T} \left(F_t n_t - C_{P_t} - C_{S_t}\right) - C_D \qquad [2.5]$$

After some substitution:

$$\max: Z = \sum_{t=1}^{T} \left(F_t N \frac{u_t(1+b) - F_t}{2bu_t} - C_{P_t} - C_{S_t}\right) - C_D \qquad [2.6]$$

Subject to:

$$0 \le n_t \le N, t = 1,2, \ldots T \qquad [2.7]$$

And

$$F_t \ge 0 \qquad [2.8]$$

2.2.1 Solution for Three Period Model

We hold certain assumptions about game parameters as shown in Table 2.5. In this model, for $T = 3$, closed form solutions exist. We can show that the solutions satisfy the sufficient conditions for optimality for Proposition 2 in Proof 2 through the Hessian matrix.

2.2.1.1 Proposition 2

If $F_1^* < A\left(2g\lambda - \frac{1}{2} g^{2/3} N^{1/3} \lambda^{2/3}\right)$, then the optimal solutions for SM1 are given by:

$$F_3^* = \frac{A\left(NF_1 + g(-2AN + F_2)\right)}{F_1 - 2A\,g\lambda} \qquad [2.9]$$

$$F_2^* = \frac{1}{4} N \left(3A - \frac{2F_1}{g\lambda}\right) \qquad [2.10]$$

$$F_1^* = \left(\frac{1}{192}\right)\left(-16A(N - 20g\lambda) - \frac{16A^2(N - 4g\lambda)^2}{D} - 16D\right) \qquad [2.11]$$

Where to simplify, let:

$$A = kC_D^{\alpha} C_S^{\beta} \qquad [2.12]$$

$$B = +6\sqrt{3}\sqrt{-A^6 g^2 N \lambda^2 (N^3 + 12gN^2\lambda + 21g^2 N \lambda^2 + 64 g^3 \lambda^3)} \qquad [2.13]$$

$$D = (A^3(N^3 + 12gN^2\lambda - 6g^2N\lambda^2 + 64g^3\lambda^3) + B)^{1/3} \qquad [2.14]$$

2.2.1.2 Proof 2

Solving:

$$\frac{\partial Z}{\partial F_3} = 0 \qquad [2.15]$$

Yields Equation 2.9. After substituting F_3 into Z, we can compute:

$$\frac{\partial^2 Z}{\partial F_1^2} = \frac{NF_1^3 - 6AgNF_1^2\lambda + Ag^2(AN(12F_1 - F_2) - 2F_2^2)\lambda^2 - 8A^3g^3N\lambda^3}{Ag\lambda(-F_1 + 2Ag\lambda)^3}, \qquad [2.16]$$

$$\frac{\partial^2 Z}{\partial F_1 \partial F_2} = \frac{\partial^2 Z}{\partial F_2 \partial F_1} = \frac{g(AN + 4F_2)\lambda}{2(F_1 - 2Ag\lambda)^2}, \qquad [2.17]$$

and

$$\frac{\partial^2 Z}{\partial F_2^2} = \frac{2g\lambda}{F_1 - 2Ag\lambda} \qquad [2.18]$$

Since F_1 must be less than the maximum utility $0 < F_1 < 2Ag\lambda$, $Ag\lambda(-F_1 + 2Ag\lambda)^3 > 0$. Thus the sign of $\frac{\partial^2 Z}{\partial F_1^2}$ is determined by the sign of the numerator:

$$C_1 = NF_1^3 - 6AgNF_1^2\lambda + Ag^2(AN(12F_1 - F_2) - 2F_2^2)\lambda^2 - 8A^3g^3N\lambda^3 \qquad [2.19]$$

To examine C_1 we compute:

$$\frac{\partial C_1}{F_1} = 3N(F_1 - 2Ag\lambda)^2 \qquad [2.20]$$

Since $\frac{\partial C_1}{F_1} > 0$, C_1 is strictly increasing in F_1. Solving:

$$\frac{\partial C_1}{F_1} = 0 \qquad [2.21]$$

Yields:

$$F_{1c} = 2Ag\lambda + \frac{(Ag^2N^2F_2(AN + 2F_2)\lambda^2)^{\frac{1}{3}}}{N} \qquad [2.22]$$

Since

$$\frac{(Ag^2N^2F_2(AN + 2F_2)\lambda^2)^{\frac{1}{3}}}{N} > 0 \qquad [2.23]$$

$F_{1c} > 2Ag\lambda$ and C_1 is negative on the range $[0, 2Ag\lambda]$. Next we compute:

$$C_2 = \frac{\partial^2 Z}{\partial F_2^2}\frac{\partial^2 Z}{\partial F_1^2} - \left(\frac{\partial^2 Z}{\partial F_2 \partial F_1}\right)^2 \qquad [2.24]$$

We must show that $C_2 \leq 0$. From Equation 2.24 above:

$$C_2 = -\frac{N\left(8F_1^3 - 48AgF_1^2\lambda + 96A^2g^2F_1\lambda^2 + A^3g^2\lambda^2(N - 64g\lambda)\right)}{4A(F_1 - 2Ag\lambda)^4} \qquad [2.25]$$

Examining the denominator of Equation 2.25, we observe that since $4A(F_1 - 2Ag\lambda)^4 > 0$. Thus, the sign is determined by

$$C_3 = -N\left(8F_1^3 - 48AgF_1^2\lambda + 96A^2g^2F_1\lambda^2 + A^3g^2\lambda^2(N - 64g\lambda)\right) \qquad [2.26]$$

We find that

$$\frac{\partial C_3}{F_1} = -24(F_1 - 2Ag\lambda)^2 \qquad [2.27]$$

And since $-24(F_1 - 2Ag\lambda)^2 < 0$, C_3 is decreasing in F_1. We find that solving $C_3 = 0$ for F_1 yields

$$F_{1d} = A\left(-\frac{1}{2}g^{2/3}N^{1/3}\lambda^{2/3} + 2g\lambda\right) \qquad [2.28]$$

For all reasonable parameter values $2g\lambda$ is much larger than $\frac{1}{2}g^{2/3}N^{1/3}\lambda^{2/3}$ and therefore, we expect that the optimal F_1^* is below $A\left(2g\lambda - \frac{1}{2}g^{2/3}N^{1/3}\lambda^{2/3}\right)$ and the proof is complete.

2.2.2 Numerical Example

As in the single purchase pricing model, with the following parameters, we find a solution where $T = 3$.

Table 2.6.1 – Subscription model numerical example

Symbol	Value	Definition
α	0.5	Relative Importance of C_D
β	0.5	Relative Importance of C_P
y	1	Relative Importance of n_{t-1}
N	5,000,000	Population Size
Q_0	n_0	Quantity Sold During Beta
g	15,000	Number of Beta Testers
C_D	600,000	Development Cost
C_P	50,000	Publishing Cost
C_S	100,000	Service Cost
λ	50	Pre-release market perception
μ	1	Customers' Expectation of Growth
δ	0.5	Retention Rate During Period
φ	0.0	Discount Rate
b	2	Spread of Uniform Distribution
k	0.00000000001	Scaling Constant

The following solution reflects the optimal values for the decision variables F_t as Z is maximized:

Table 2.6.2 – Optimal prices

Decision Variable	Value
$\boldsymbol{F_1}$	1.11
$\boldsymbol{F_2}$	12.89
$\boldsymbol{F_3}$	7.29
$\boldsymbol{Z}$	48,370,933

The values for certain important variables as they change by period are in Table 2.6.3.

Table 2.6.3 – Period values

Variable	Value	Variable	Value
U_1	1.84	n_1	6,513,198
U_2	15.95	n_2	2,979,795
U_3	7.30	n_3	2,500,000
Z_1	-7,392,472		
Z_2	38,265,962		
Z_3	18,097,443		

2.3 Conclusion

The previous sections present a mathematical model for both a single purchase and subscription pricing strategies and provide a numerical example for each. We present a solution for each model that satisfies the necessary optimality conditions. While the two models give numerical results, direct comparison of the amount charged as a single price or the subscription fee charged is not possible due to the nature of the utility functions. However, the reader can compare the amount of total revenue earned through the use of each model. The next chapter presents a numerical experiment that tests these models' sensitivity to the various parameters discussed in the earlier sections and concludes with a discussion of the managerial implications of the findings of this experiment.

CHAPTER 3: NUMERICAL EXPERIMENT

3.1 Single Purchase Model

3.1.1 Single Purchase Model With No Growth Expectation

In this experiment we varied the game parameters and found the optimal pricing strategy for each the parameter combinations shown in Table 3.1.1. For this experiment, we held μ and φ constant at $\mu = 1$ and $\varphi = 0$ (no customers' growth expectation and no discounting respectively). When the customer does not expect a particular game to become more popular than it already is, μ is 1. However, when the opposite is the case and a game is of a type that is becoming fashionable or otherwise trending upwards in popularity, μ is much larger than 1.

The results from the experiments are shown in Table 3.1.2. Table 3.1.3 is obtained from Table 3.1.2 and shows the profit per period as a percentage of the total profit and the quantity sold per period as a percentage of the total quantity sold. Table 3.1.3 also shows the price charged per period relative to the maximum price charged over the three periods, which is normalized to 1. The results are illustrated in Figures 3.1.1 – 3.1.12.

Of all the parameters that we varied (C_D, C_P, C_S, α, N, g, λ, and δ), we found N, g, λ, and δ to have significant effects. Results produced by the model are consistent with patterns shown by certain games already in the market; see Table 3.1.2. For all parameter combinations tested, certain trends hold:

- No pricing strategy completely clears the market
- The quantity sold per period is decreasing in time t
- Initial period parameters (g and λ) do not have impacts that last beyond the price set in the first period
- A low introductory price to maximize sales is followed with a price that maximizes profit which is in turn followed by a final low price, an exception concerning market size is noted below

The changes in the pricing strategy as a result of changes in the parameter N reflect the importance of proper pricing strategy with respect to the potential market size. Large values of N result in the pricing strategy changing from a high introductory price to an introductory price that is considerably lower. This pricing of games with small potential market in which large prices are charged in the first period runs counter to the “normal” pricing strategy of beginning with a low price to increase the number of players and increasing price as the customers’ utilities increase. This change in the pricing strategy for games with small potential market is shown in Figure 3.1.2. A small potential market makes it difficult to sell a large quantity in the first period and increase the price in period two to capitalize on the increased utility.

Table 3.1.1 – Parameter values for numerical experiment

Parameter	Level	Value
C_D	Low	200,000
	Medium	600,000
	High	1,000,000
C_P	Low	10,000
	Medium	50,000
	High	90,000
C_S	Low	50,000
	Medium	100,000
	High	150,000
α	Low	0.2
	Medium	0.5
	High	0.8
N	Low	2,000,000
	Medium	5,000,000
	High	8,000,000
g	Low	5,000
	Medium	15,000
	High	25,000
λ	Low	20
	Medium	50
	High	80
δ	Low	0.2
	Medium	0.5
	High	0.8

The parameters C_D, C_P, C_S, and α, were found to have little impact on the pricing strategy or the quantity sold in different periods as illustrated in Table 3.1.2. We did find that other parameters or game characteristics had a significant impact on the pricing strategy and the profit earned. We found that varying N, g, λ, and δ resulted in considerable changes in prices and quantities sold in different periods as illustrated in Tables 3.1.2 and Table 3.1.3. We now examine the effects of these parameters in greater detail.

Table 3.1.2 – Single purchase experiment results

Parameter Levels	Q_1*	Q_2*	Q_3*	$\sum Q$*	P_1	P_2	P_3	Z^*
Low C_D	2,299	1,270	708	4,277	$ 3.34	$ 6.86	$ 3.42	$ 21,030
Medium C_D	2,299	1,270	708	4,277	$ 6.27	$ 12.87	$ 6.42	$ 39,622
High C_D	2,299	1,270	708	4,277	$ 8.59	$ 17.63	$ 8.79	$ 54,257
Low C_P	2,299	1,270	708	4,277	$ 6.07	$ 12.45	$ 6.21	$ 38,423
Medium C_P	2,299	1,270	708	4,277	$ 6.07	$ 12.45	$ 6.21	$ 38,303
High C_P	2,299	1,270	708	4,277	$ 6.07	$ 12.45	$ 6.21	$ 38,183
Low C_S	2,299	1,270	708	4,277	$ 4.75	$ 9.74	$ 4.86	$ 29,887
Medium C_S	2,299	1,270	708	4,277	$ 6.17	$ 12.67	$ 6.32	$ 38,990
High C_S	2,299	1,270	708	4,277	$ 7.28	$ 14.95	$ 7.45	$ 46,032
Low α	2,299	1,270	708	4,277	$ 3.25	$ 6.66	$ 3.32	$ 19,995
Medium α	2,299	1,270	708	4,277	$ 5.43	$ 11.14	$ 5.55	$ 34,146
High α	2,299	1,270	708	4,277	$ 9.53	$ 19.56	$ 9.75	$ 60,768
Low N	942	493	275	1,710	$ 5.96	$ 5.13	$ 2.48	$ 7,853
Medium N	2,307	1,266	706	4,279	$ 6.09	$ 12.49	$ 6.21	$ 33,436
High N	3,650	2,050	1,142	6,842	$ 6.16	$ 19.74	$ 9.94	$ 73,621
Low g	2,251	1,298	723	4,272	$ 2.09	$ 12.16	$ 6.21	$ 28,852
Medium g	2,309	1,265	705	4,280	$ 6.09	$ 12.51	$ 6.21	$ 38,307
High g	2,339	1,246	695	4,280	$ 10.03	$ 12.70	$ 6.20	$ 47,750
Low λ	2,252	1,292	720	4,265	$ 2.49	$ 12.20	$ 6.21	$ 29,745
Medium λ	2,307	1,266	706	4,279	$ 6.09	$ 12.50	$ 6.21	$ 38,296
High λ	2,339	1,251	698	4,287	$ 9.62	$ 12.67	$ 6.21	$ 46,868
Low δ	2,290	1,318	689	4,296	$ 6.08	$ 11.99	$ 4.55	$ 36,724
Medium δ	2,300	1,269	708	4,277	$ 6.07	$ 12.45	$ 6.20	$ 38,285
High δ	2,309	1,221	727	4,258	$ 6.06	$ 12.92	$ 7.88	$ 39,901

* in thousands

Table 3.1.3 – Single purchase experiment results analysis

Parameter Levels	Z_1/Z	Z_2/Z	Z_3/Z	P_1/P_{Max}	P_2/P_{Max}	P_3/P_{Max}	$Q_1/\sum Q$	$Q_2/\sum Q$	$Q_3/\sum Q$
Low C_D	36%	50%	14%	49%	100%	50%	54%	30%	17%
Medium C_D	36%	50%	14%	49%	100%	50%	54%	30%	17%
High C_D	36%	50%	14%	49%	100%	50%	54%	30%	17%
Low C_P	36%	50%	14%	49%	100%	50%	54%	30%	17%
Medium C_P	36%	50%	14%	49%	100%	50%	54%	30%	17%
High C_P	36%	50%	14%	49%	100%	50%	54%	30%	17%
Low C_S	36%	50%	14%	49%	100%	50%	54%	30%	17%
Medium C_S	36%	50%	14%	49%	100%	50%	54%	30%	17%
High C_S	36%	50%	14%	49%	100%	50%	54%	30%	17%
Low α	36%	50%	14%	49%	100%	50%	54%	30%	17%
Medium α	36%	50%	14%	49%	100%	50%	54%	30%	17%
High α	36%	50%	14%	49%	100%	50%	54%	30%	17%
Low N	66%	28%	6%	100%	86%	42%	55%	29%	16%
Medium N	42%	46%	13%	49%	100%	50%	54%	30%	17%
High N	31%	54%	15%	31%	100%	50%	53%	30%	17%
Low g	16%	66%	19%	17%	100%	51%	53%	30%	17%
Medium g	36%	50%	14%	49%	100%	50%	54%	30%	16%
High g	49%	40%	11%	79%	100%	49%	55%	29%	16%
Low λ	18%	64%	18%	20%	100%	51%	53%	30%	17%
Medium λ	36%	50%	14%	49%	100%	50%	54%	30%	16%
High λ	48%	41%	11%	76%	100%	49%	55%	29%	16%
Low δ	38%	52%	10%	51%	100%	38%	53%	31%	16%
Medium δ	36%	50%	14%	49%	100%	50%	54%	30%	17%
High δ	35%	48%	17%	47%	100%	61%	54%	29%	17%

3.1.2 Effects of Game and Environmental Characteristics

3.1.2.1 Population Size ($\boldsymbol{N}$)

For low values of N, the publisher will start with a high price, thus obtaining the majority of profits in the first period; see Figure 3.1.1. This is because the market size is small and the publisher cannot significantly increase the utility of the game for the consumers without selling to most of them and eroding future potential revenues. For higher values of N, the publisher is able to increase the utility of the game in the second period by increasing the size of the player base in the first period, while still retaining large revenue potential due to the large market size. During period 1, for all values of N tested, the publisher will sell the most copies, with subsequent periods having sales that are decreasing over time; see Figure 3.1.3.

Of all the parameters tested, N is the only parameter found that will cause a change in the pricing pattern and reduce the ability of the publisher to use network externalities to increase profits. These characteristics of the parameter N suggest that for a small game, one which has a limited market or potential fan base, it is best to follow a strategy of higher prices in earlier periods similar to a skimming strategy where a publisher gradually lowers price over time in order to capture the maximum amount of consumer surplus.

Figure 3.1.1 shows that most of the profit for small games is earned in early periods. For all values of N tested, we find that Q_t is decreasing in t, see Figure 3.1.3. This is due to the need to sell a large number of copies of the game early in its lifecycle in order to maximize consumer utility through network externalities.

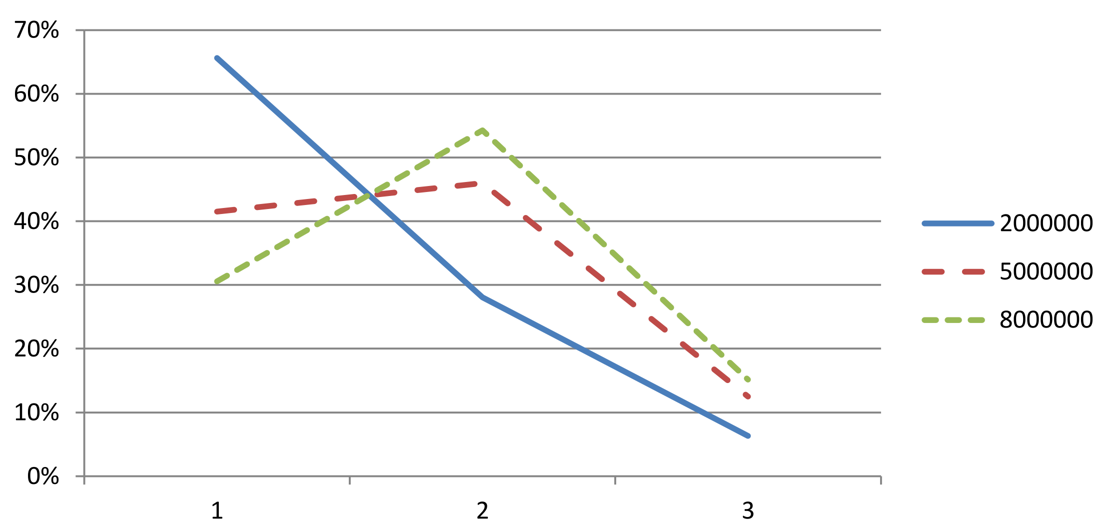

Figure 3.1.1: Single purchase Z_t/Z over time for different market sizes

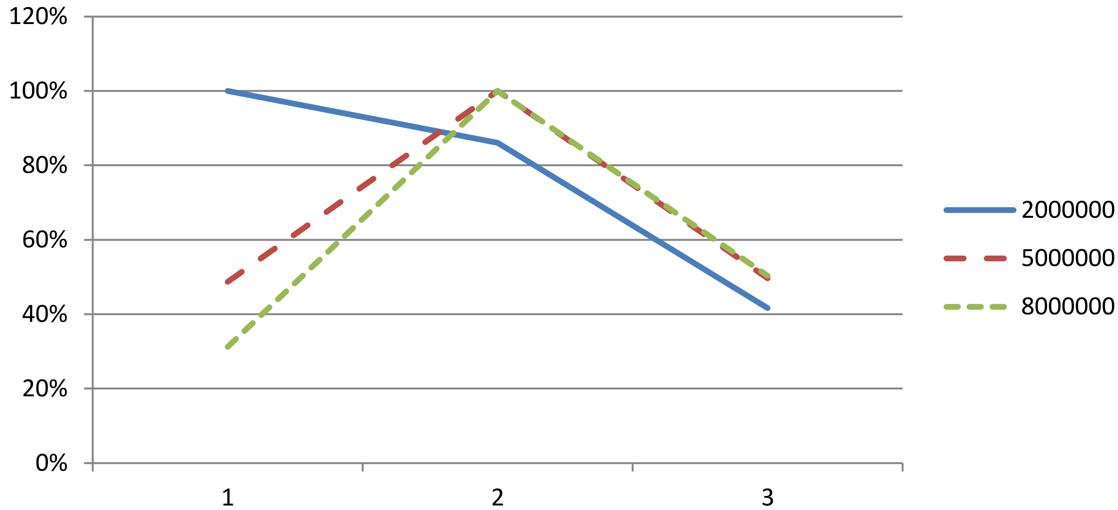

Figure 3.1.2: Single purchase P_t/P_{Max} over time for different market sizes

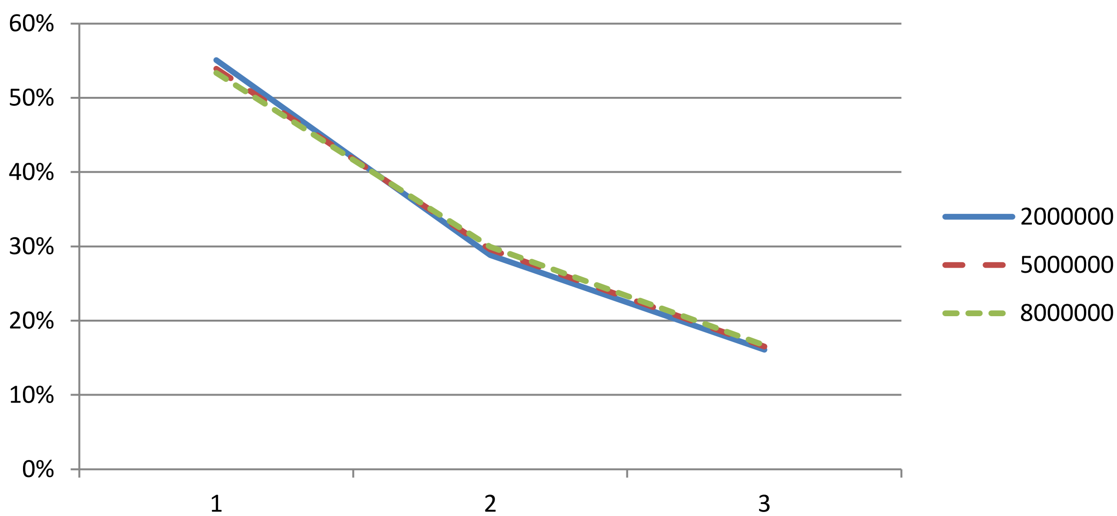

Figure 3.1.3: Single purchase Q_t/Q over time for different market sizes

3.1.2.2 Beta Test Group Size ($\boldsymbol{g}$)

For low values of g, initial consumer utility is low and therefore the game publisher introduces a low price to increase utility via quantity sold. The percentage of total profit earned in period 1 increases alongside rising values for g, see Figure 3.1.4, since larger g means higher initial consumer utility. Prices in periods two and three do not appreciably change with respect to the same increases in g, see Figure 3.1.5, due to the fact that customer utility is increased as a result of the expanded beta test group size. As was the case for N, the percentage of copies sold in each period relative to all periods combined does not change significantly with respect to g as is shown in Figure 3.1.6. This stems from the publisher's need to maximize consumer utility in the first period. Again, similar to N, values of g above a certain level may cause the publisher to set the price at a point that runs counter to traditional considerations about the impact of network externalities. When g is large, the prices in the first two periods become closer to each other.

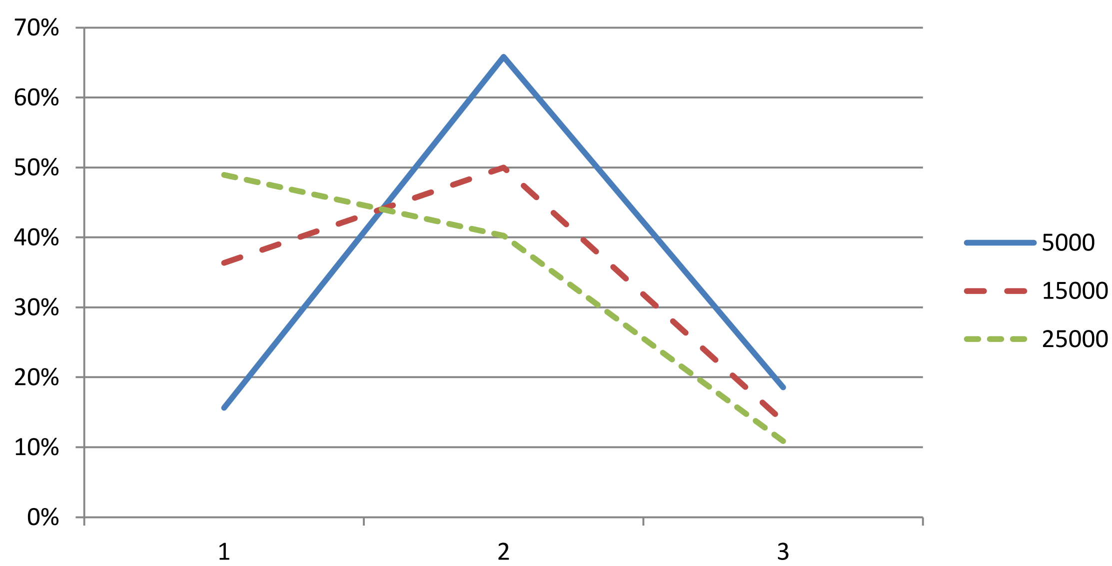

Figure 3.1.4: Single purchase Z_t/Z over time for different beta test group sizes

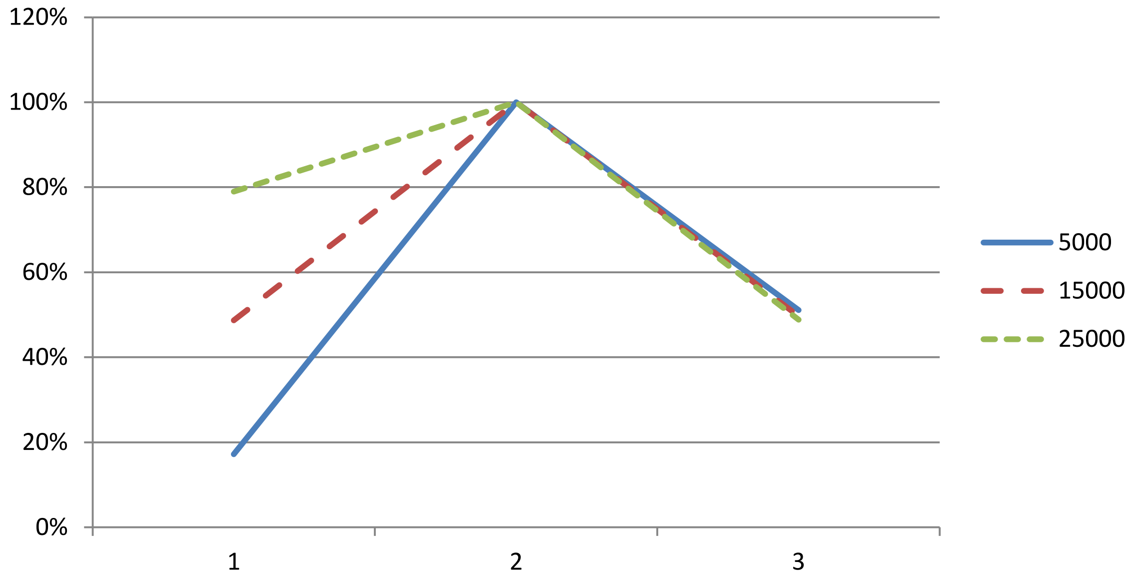

Figure 3.1.5: Single purchase P_t/P_{Max} over time for different beta test group sizes

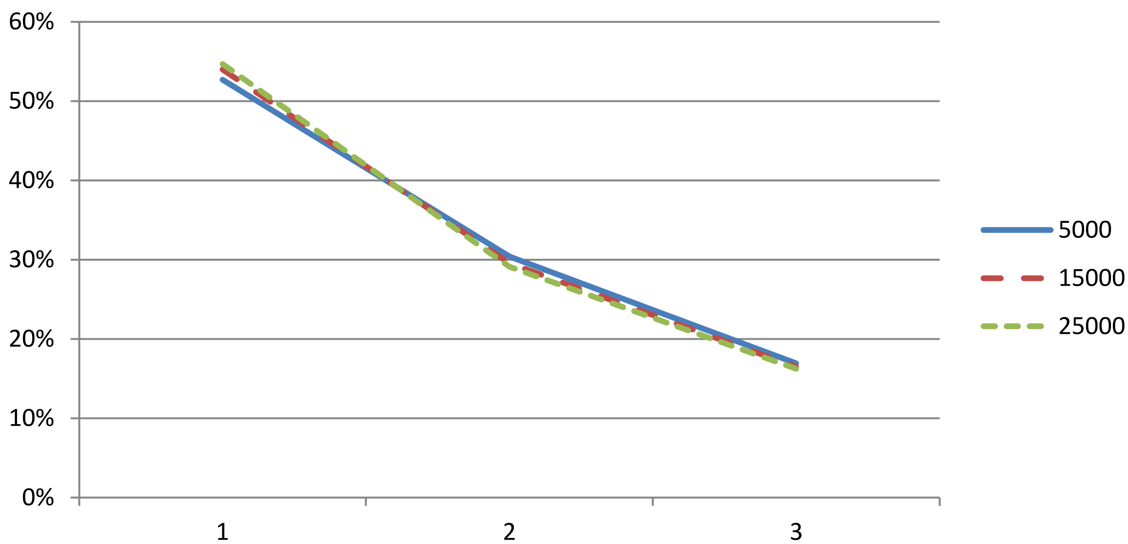

Figure 3.1.6: Single purchase Q_t/Q over time for different beta test group sizes

3.1.2.3 Pre-Release Market Perception Coefficient ($\boldsymbol{\lambda}$)

As with the beta group test size, the percentage of total profit earned in period 1 increases alongside increases in the pre-release market perception coefficient λ, see Figure 3.1.7. This is because the publisher is able to price the game at a relatively high price in early periods when initial demand is high, see Figure 3.1.8. Additionally, the price in the first period changes with respect to changing values for λ while prices in subsequent periods do not appreciably change with respect the same increases in λ because this parameter mostly impacts customer utility in the first period. λ exhibits the same impact on the pricing behavior as the aforementioned parameters as measured by percentage of quantity sold relative to total quantity sold, Figure 3.1.9, as the publisher must price the game so as to achieve a maximum number of sales in the early periods to take advantage of network externalities. Certain games are in a genre that is particularly popular at one particular time or another. That, when combined with a proper level of marketing effort (C_P), will result in a game's release being more anticipated or more eagerly looked forward to by potential players. The model does not consider this relationship in its current form. Additionally, professional reviews or hype surrounding a game's release contribute to the popularity of a game during its initial phases.

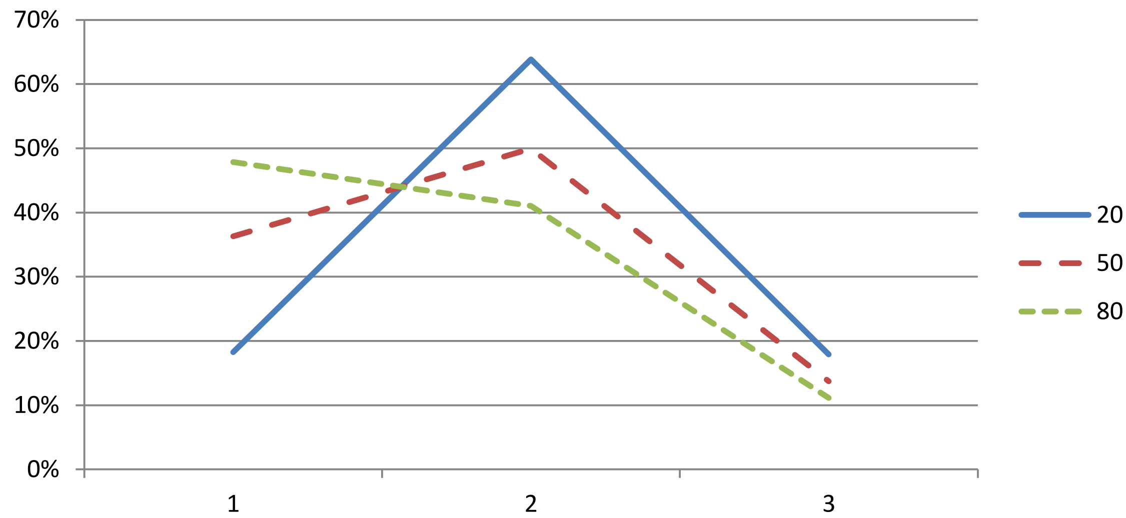

Figure 3.1.7: Single purchase Z_t/Z over time for different λ

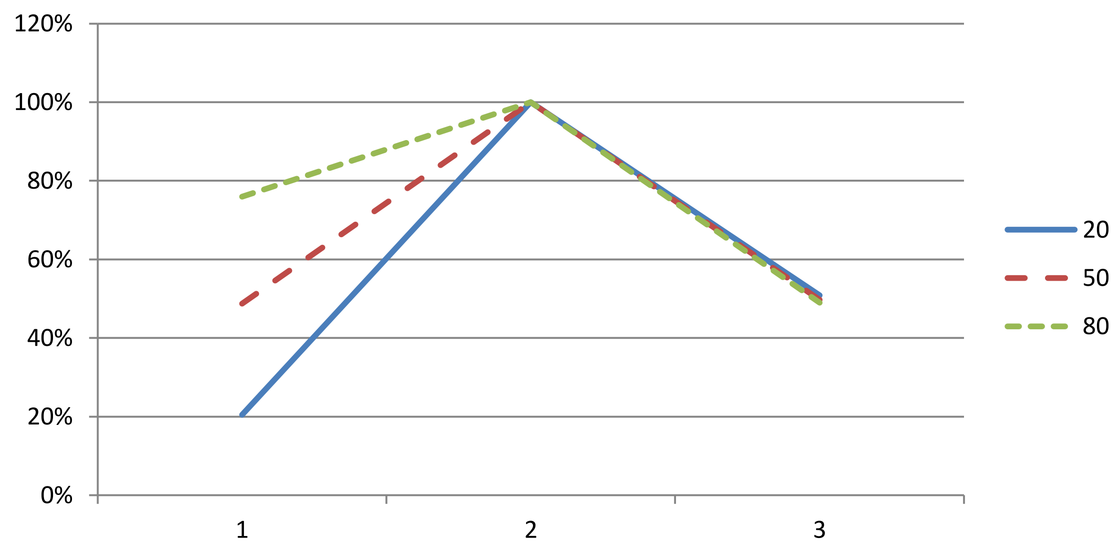

Figure 3.1.8: Single purchase P_t/P_{Max} over time for different λ

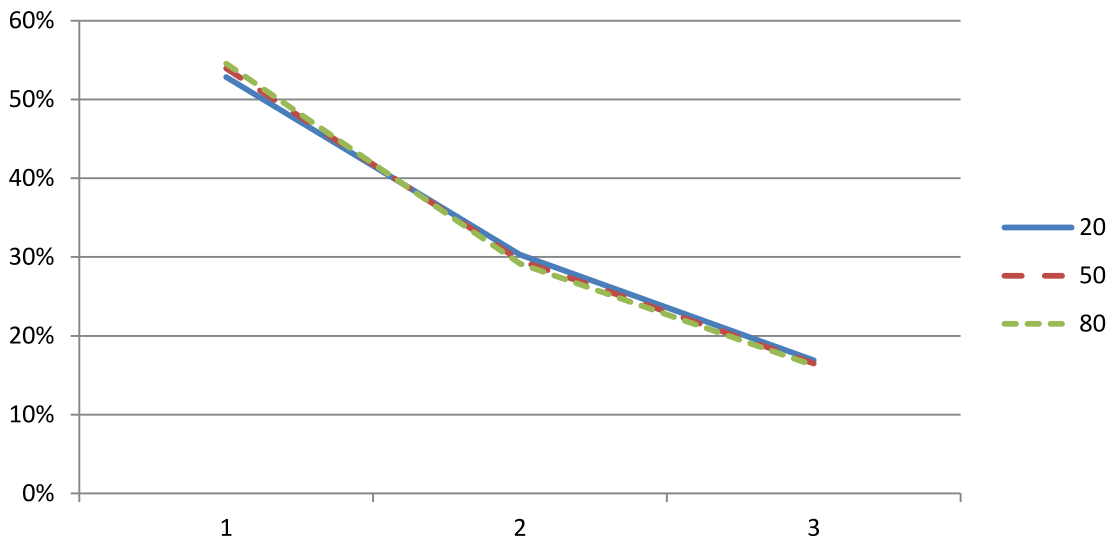

Figure 3.1.9: Single purchase Q_t/Q over time for different λ

3.1.2.4 Retention Rate ($\boldsymbol{\delta}$)

Increased retention rate (δ) values result in a lower percentage of profits for the initial two periods, however, the final period will experience increased percentage of total profit relative to the different changes in δ; refer to Figure 3.1.10. This is because the game publisher is assured of a higher level of utility for the consumer so long as retention rates remain high. Also, the values for δ have little impact on the prices charged for the first two periods, but result in considerable changes in the prices charged for the final period, see Figure 3.1.11, as the publisher is able to charge a higher price in the final period because of the increased utility stemming from a high retention rate. Finally, the percentage of quantity sold relative to total quantity sold reflects its largest change when varying δ, particularly for the second period when compared to the earlier parameters' effects on the second period, see Figure 3.1.12. While retention rate cannot directly impact the price set in the initial period, subsequent periods have a higher level of consumer utility and as such will have a higher price set by the publisher. For players who are retained by the game, they contribute to the overall utility of purchasers in subsequent periods. For periods n_t $t > 1$, player retention becomes increasingly important. As with all products that exhibit network externalities, the price charged is a function of the size of the player base and as such, a greater player base will result in the publisher being able to charge a higher price.

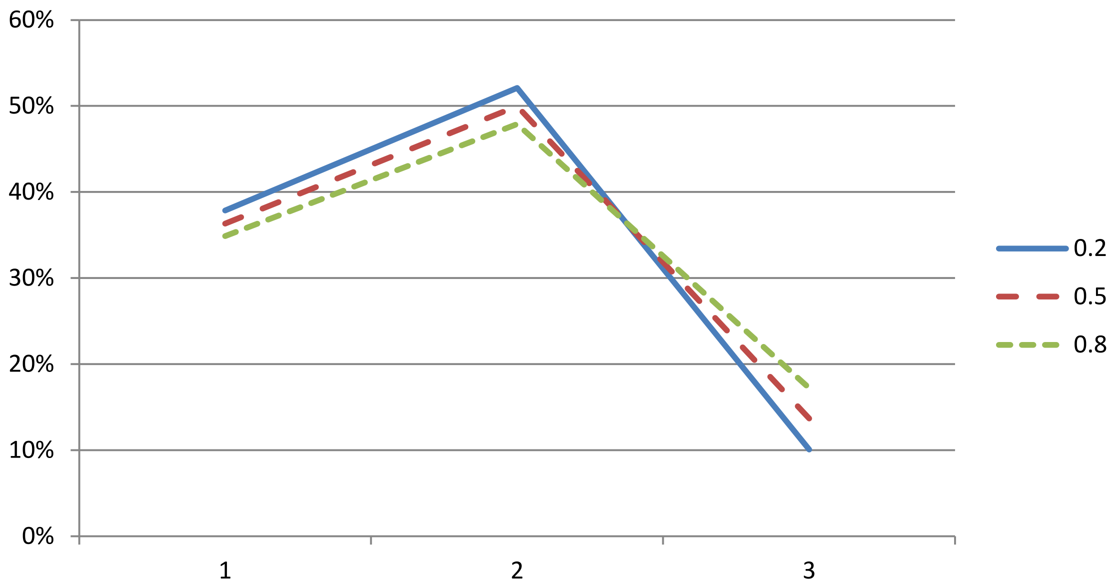

Figure 3.1.10: Single purchase Z_t/Z over time for different retention rates

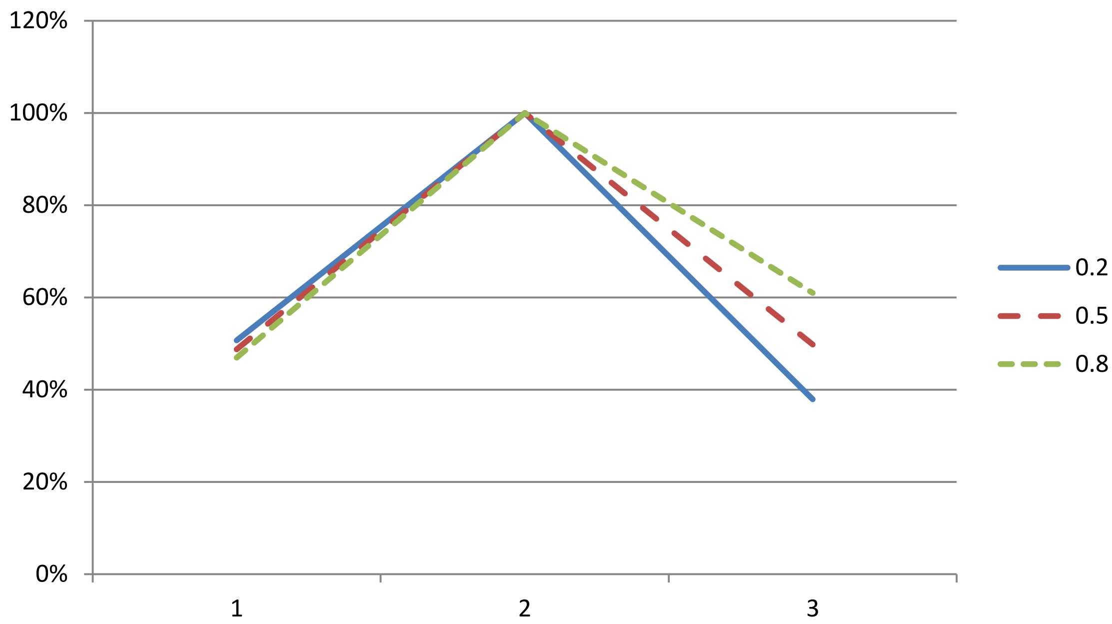

Figure 3.1.11: Single purchase P_t/P_{Max} over time for different retention rates

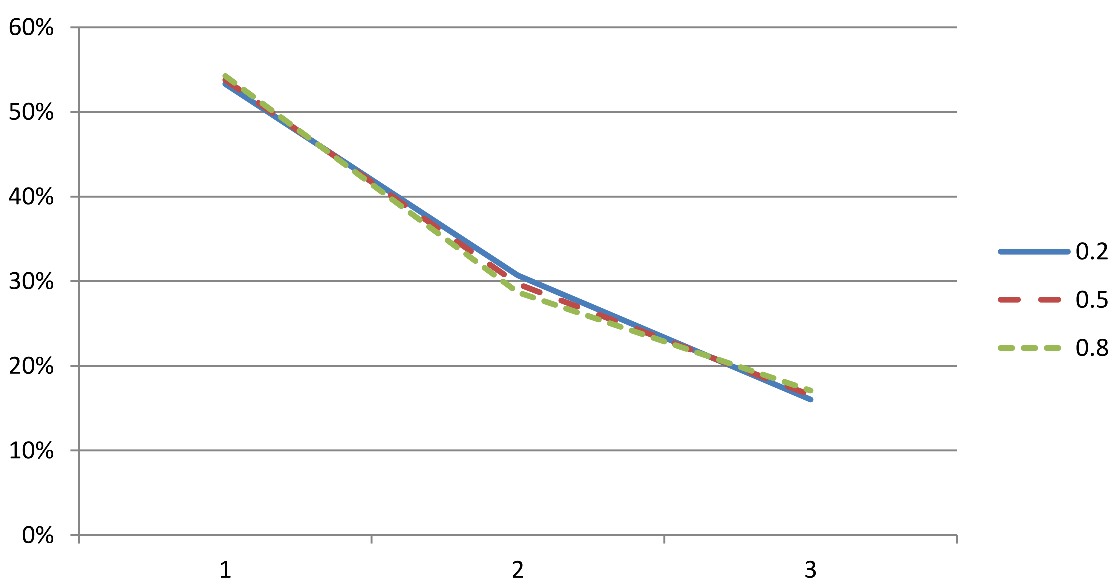

Figure 3.1.12: Single purchase Q_t/Q over time for different retention rates

3.1.3 Single Purchase Model with Moderate Growth Expectations

For this experiment, we used a customer growth expectation of $\mu = 3$. This resulted in several changes in the patterns observed earlier as shown in Tables 3.1.4 and 3.1.5. Because of higher growth expectations, the publisher does not have to rely as heavily on actual network externalities and can charge a higher price in earlier periods and the majority of profit is earned in the first period with significantly less being earned in subsequent periods. As shown in Figures 3.1.13 and 3.1.14, for small and medium sized markets, for certain parameters, the game is initially priced higher and then is priced low in the final period due to the game publisher being able to use the customer growth expectation. This results in a majority of the profit being earned early in the game's lifecycle. For small beta test group sizes, the game must be priced low because the publisher needs a large number of sales in order to build customer utility in the following periods. This means that the greatest amount of revenue is earned in the following period as actual network externalities begin to have an effect on the customer utility instead of only customer expectations, see Figures 3.1.15 and 3.1.16. For medium and high levels of beta test group sizes the game publisher prices the product higher as network externalities have less impact in the second period. The retention rate of customers does not have as significant an impact in this experiment as the customers' own expectation of growth overrides some of the impacts that a low retention rate can have on customer utility via network externalities, see Figures 3.1.17 and 3.1.18. For all parameters tested in this experiment, the effects are such that the quantity sold by the publisher is decreasing as t increases and other patterns noted in the previous section hold.

Table 3.1.4 – Single purchase experiment results ($\mu = 3$)

Parameter Levels	Q_1*	Q_2*	Q_3*	$\sum Q$*	P_1	P_2	P_3	Z^*
Low C_D	2420	1245	660	4325	$ 13.99	$ 14.09	$ 3.47	$ 58,171.02
Medium C_D	2420	1245	660	4325	$ 26.25	$ 26.43	$ 6.51	$ 109,299.33
High C_D	2420	1245	660	4325	$ 35.95	$ 36.20	$ 8.91	$ 149,692.39
Low C_P	2420	1245	660	4325	$ 25.40	$ 25.58	$ 6.29	$ 105,840.91
Medium C_P	2420	1245	660	4325	$ 25.40	$ 25.58	$ 6.29	$ 105,720.91
High C_P	2420	1245	660	4325	$ 25.40	$ 25.58	$ 6.29	$ 105,600.91
Low C_S	2420	1245	660	4325	$ 19.87	$ 20.01	$ 4.92	$ 82,630.50
Medium C_S	2420	1245	660	4325	$ 25.84	$ 26.02	$ 6.40	$ 107,585.18
High C_S	2420	1245	660	4325	$ 30.48	$ 30.70	$ 7.55	$ 126,947.06
Low α	2420	1245	660	4325	$ 13.58	$ 13.68	$ 3.37	$ 56,047.40
Medium α	2420	1245	660	4325	$ 22.71	$ 22.87	$ 5.63	$ 94,442.60
High α	2420	1245	660	4325	$ 39.89	$ 40.18	$ 9.89	$ 166,672.75
Low N	976	490	260	1725	$ 25.20	$ 10.36	$ 2.51	$ 29,383.15
Medium N	2424	1243	659	4326	$ 25.42	$ 25.62	$ 6.29	$ 97,052.75
High N	3859	2003	1062	6923	$ 25.56	$ 40.74	$ 10.08	$ 190,726.84
Low g	2395	1262	669	4326	$ 8.60	$ 25.26	$ 6.30	$ 64,461.64
Medium g	2427	1242	659	4327	$ 25.43	$ 25.65	$ 6.29	$ 105,769.83
High g	2438	1231	653	4322	$ 42.16	$ 25.82	$ 6.29	$ 146,931.27
Low λ	2394	1258	667	4318	$ 10.29	$ 25.30	$ 6.29	$ 68,465.90
Medium λ	2425	1242	659	4326	$ 25.42	$ 25.63	$ 6.29	$ 105,715.64
High λ	2440	1235	655	4330	$ 40.47	$ 25.79	$ 6.30	$ 142,981.20
Low δ	2419	1268	649	4336	$ 25.39	$ 25.08	$ 4.48	$ 104,137.77
Medium δ	2420	1245	660	4325	$ 25.40	$ 25.58	$ 6.29	$ 105,710.69
High δ	2421	1222	671	4314	$ 25.40	$ 26.07	$ 8.11	$ 107,314.28

* in thousands

Table 3.1.5 – Single purchase experiment results analysis ($\mu = 3$)

Parameter Levels	Z_1/Z	Z_2/Z	Z_3/Z	P_1/P_{Max}	P_2/P_{Max}	P_3/P_{Max}	$Q_1/\sum Q$	$Q_2/\sum Q$	$Q_3/\sum Q$
Low $\boldsymbol{C_D}$	58%	37%	5%	99%	100%	25%	56%	29%	15%
Medium $\boldsymbol{C_D}$	58%	37%	5%	99%	100%	25%	56%	29%	15%
High $\boldsymbol{C_D}$	58%	37%	5%	99%	100%	25%	56%	29%	15%
Low $\boldsymbol{C_P}$	58%	37%	5%	99%	100%	25%	56%	29%	15%
Medium $\boldsymbol{C_P}$	58%	37%	5%	99%	100%	25%	56%	29%	15%
High $\boldsymbol{C_P}$	58%	37%	5%	99%	100%	25%	56%	29%	15%
Low $\boldsymbol{C_S}$	58%	37%	5%	99%	100%	25%	56%	29%	15%
Medium $\boldsymbol{C_S}$	58%	37%	5%	99%	100%	25%	56%	29%	15%
High $\boldsymbol{C_S}$	58%	37%	5%	99%	100%	25%	56%	29%	15%
Low $\boldsymbol{\alpha}$	58%	37%	5%	99%	100%	25%	56%	29%	15%
Medium $\boldsymbol{\alpha}$	58%	37%	5%	99%	100%	25%	56%	29%	15%
High $\boldsymbol{\alpha}$	58%	37%	5%	99%	100%	25%	56%	29%	15%
Low $\boldsymbol{N}$	82%	16%	2%	100%	41%	10%	57%	28%	15%
Medium $\boldsymbol{N}$	63%	32%	4%	99%	100%	25%	56%	29%	15%
High $\boldsymbol{N}$	52%	43%	6%	63%	100%	25%	56%	29%	15%
Low $\boldsymbol{g}$	32%	61%	8%	34%	100%	25%	55%	29%	15%
Medium $\boldsymbol{g}$	58%	37%	5%	99%	100%	25%	56%	29%	15%
High $\boldsymbol{g}$	70%	27%	3%	100%	61%	15%	56%	28%	15%
Low $\boldsymbol{\lambda}$	36%	57%	7%	41%	100%	25%	55%	29%	15%
Medium $\boldsymbol{\lambda}$	58%	37%	5%	99%	100%	25%	56%	29%	15%
High $\boldsymbol{\lambda}$	69%	27%	3%	100%	64%	16%	56%	29%	15%
Low $\boldsymbol{\delta}$	59%	38%	3%	100%	99%	18%	56%	29%	15%
Medium $\boldsymbol{\delta}$	58%	37%	5%	99%	100%	25%	56%	29%	15%
High $\boldsymbol{\delta}$	57%	36%	6%	97%	100%	31%	56%	28%	16%

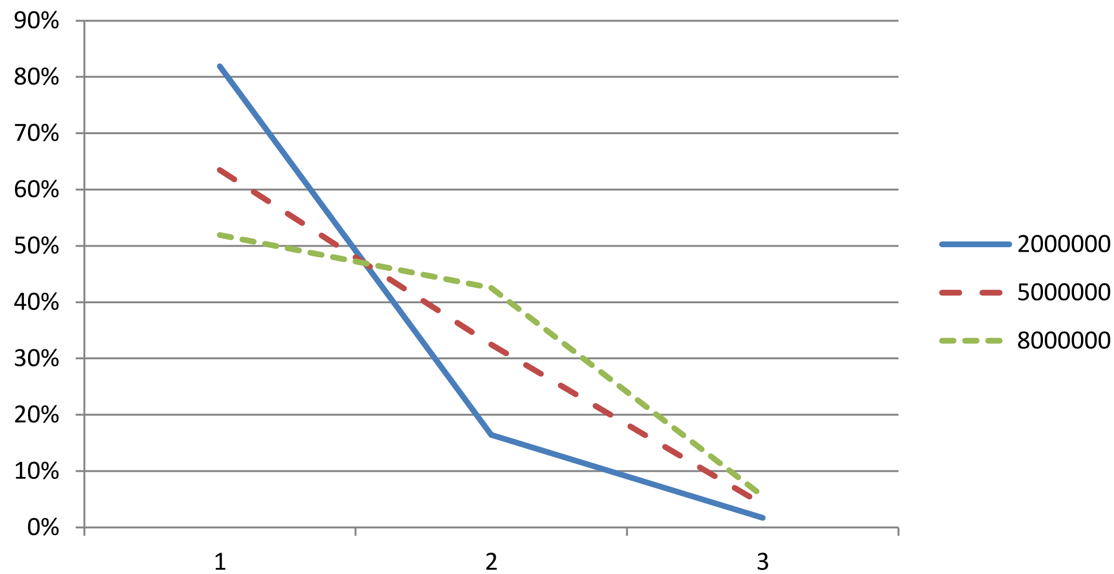

Figure 3.1.13: Single purchase Z_t/Z over time for different market sizes ($\mu = 3$)

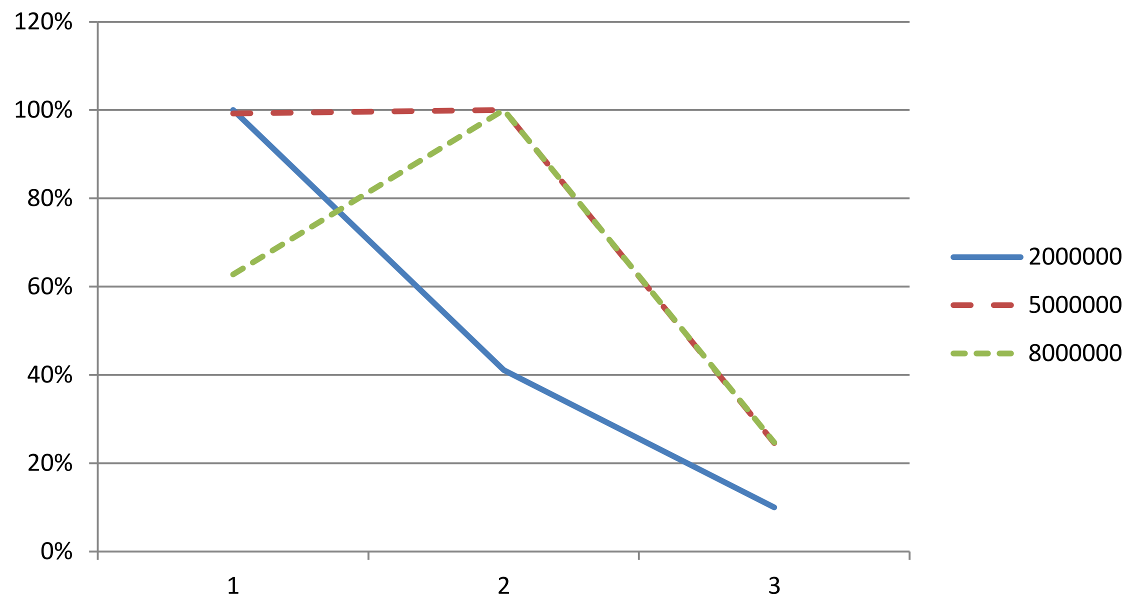

Figure 3.1.14: Single purchase P_t/P_{Max} over time for different market sizes ($\mu = 3$)

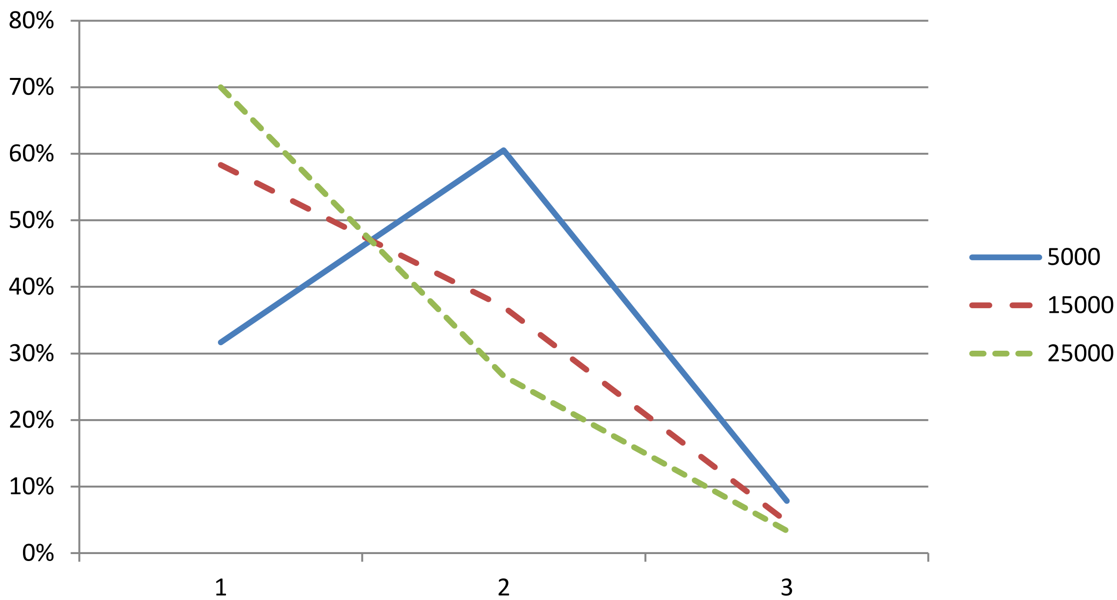

Figure 3.1.15: Single purchase Z_t/Z over time for different g where $\mu = 3$

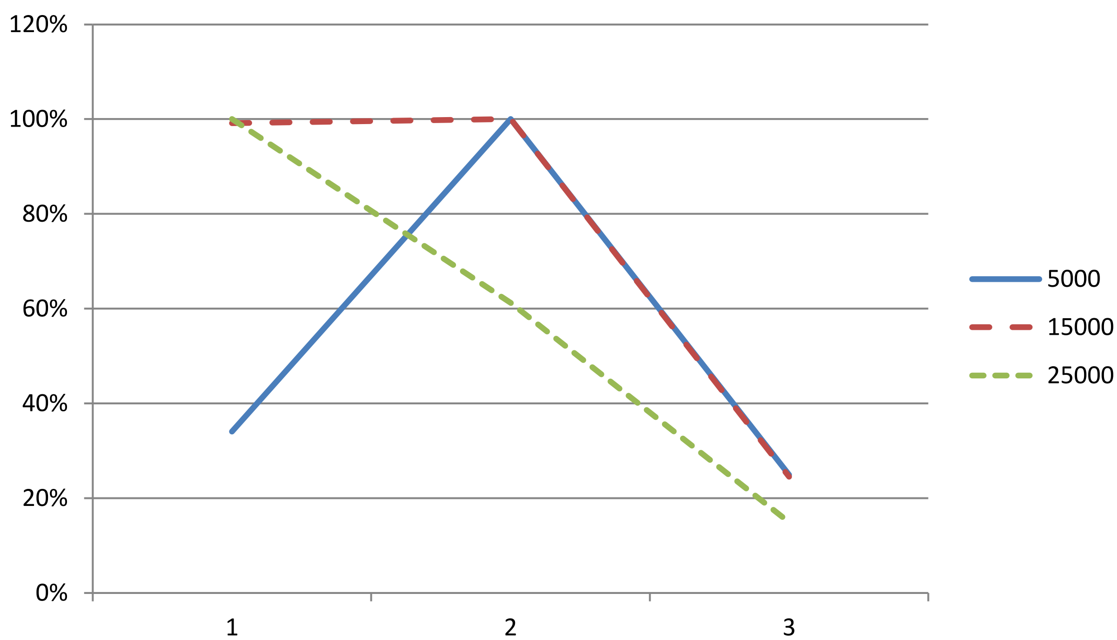

Figure 3.1.16: Single purchase P_t/P_{Max} over time for different g where $\mu = 3$

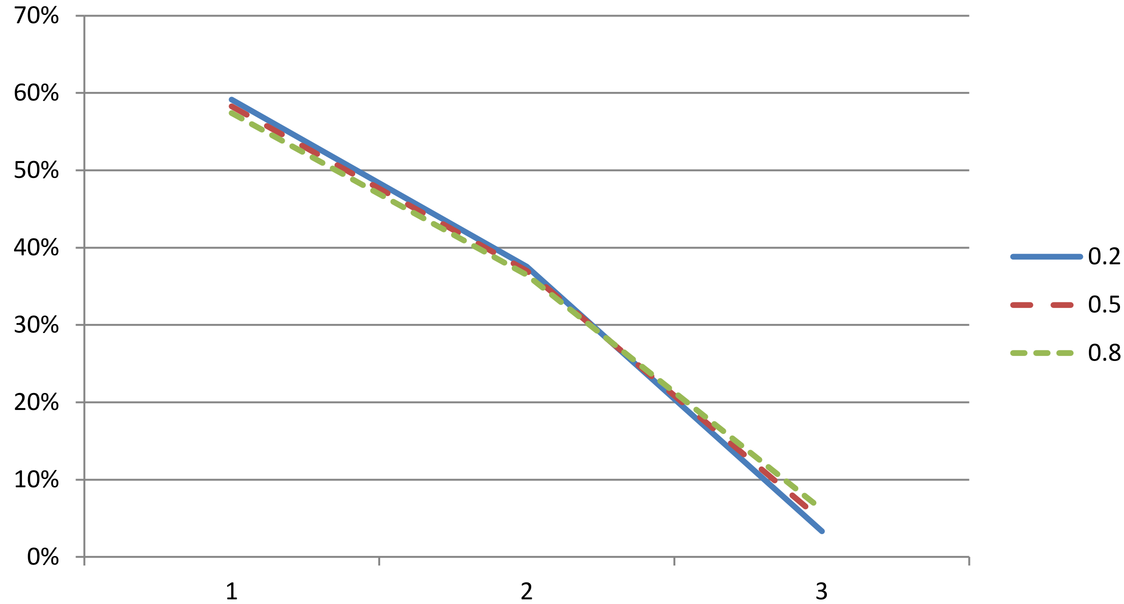

Figure 3.1.17: Single purchase Z_t/Z over time for different retention rates ($\mu = 3$)

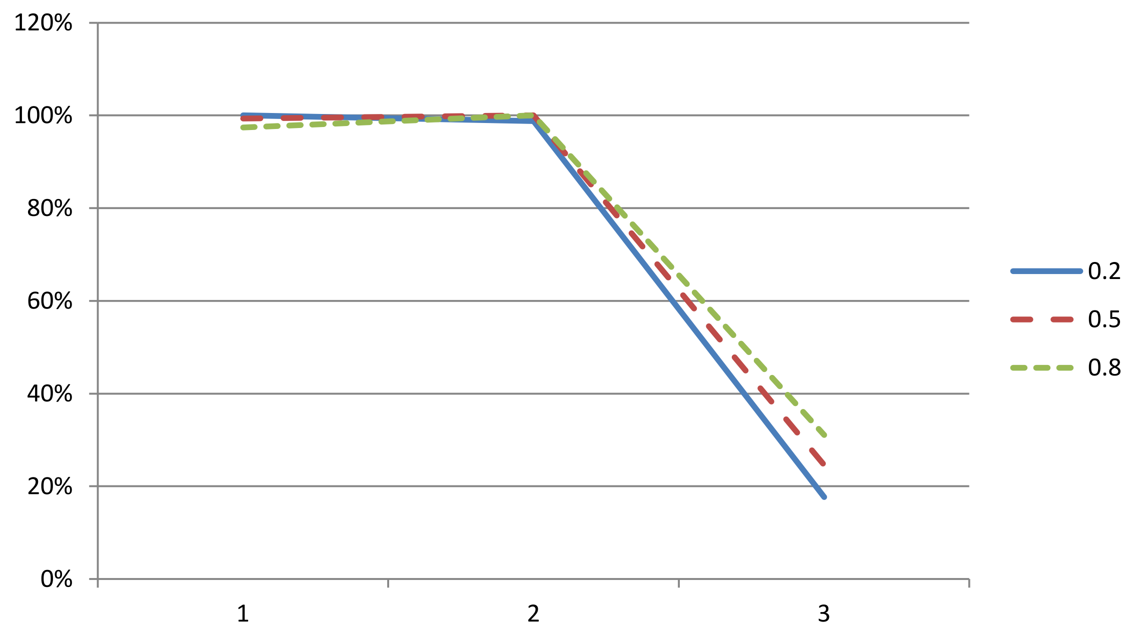

Figure 3.1.18: Single purchase P_t/P_{Max} over time for different retention rates ($\mu = 3$)

3.1.4 Single Purchase Model with High Growth Expectation

For this experiment, we set the customer growth expectation at $\mu = 5$. A high level of customer growth expectation results in significant differences between the results of this experiment and those discussed in Sections 3.1.1 and 3.1.2. The results of this experiment are shown in Tables 3.1.6 and 3.1.7. In this experiment the profit earned in the first period is significantly higher than in previous experiments which are driven by the publisher charging the highest price in the first period due to the increased growth expectation. For small and medium sized markets, network externalities are rendered meaningless as the customers' utility function is dominated by the expectation of growth. This means that a game is priced high in initial periods and is priced low in the final period with a majority of the profit being earned in the initial period, see Figures 3.1.19 and 3.1.20. For large market sizes, the price does not begin to decline until the final pricing period. This is because the customers expect a significant portion of the available market to purchase the game. With the exception of small beta test group sizes, the game publisher will also price the game high in the initial period with subsequent periods seeing a reduced price, see Figures 3.1.21 and 3.1.22.

Table 3.1.6 – Single purchase experiment results ($\mu = 5$)

Parameter Levels	Q_1*	Q_2*	Q_3*	$\sum Q$*	P_1	P_2	P_3	Z^*
Low C_D	2453	1240	646	4339	$ 33.07	$ 21.23	$ 3.48	$ 116,440
Medium C_D	2453	1240	646	4339	$ 62.04	$ 39.83	$ 6.54	$ 218,614
High C_D	2453	1240	646	4339	$ 84.97	$ 54.56	$ 8.95	$ 299,417
Low C_P	2453	1240	646	4339	$ 60.03	$ 38.54	$ 6.33	$ 211,610
Medium C_P	2453	1240	646	4339	$ 60.03	$ 38.54	$ 6.33	$ 211,490
High C_P	2453	1240	646	4339	$ 60.03	$ 38.54	$ 6.33	$ 211,370
Low C_S	2453	1240	646	4339	$ 46.96	$ 30.15	$ 4.95	$ 165,378
Medium C_S	2453	1240	646	4339	$ 61.07	$ 39.22	$ 6.44	$ 215,201
High C_S	2453	1240	646	4339	$ 72.04	$ 46.26	$ 7.59	$ 253,892
Low α	2453	1240	646	4339	$ 32.10	$ 20.61	$ 3.38	$ 112,609
Medium α	2453	1240	646	4339	$ 53.69	$ 34.47	$ 5.66	$ 189,040
High α	2453	1240	646	4339	$ 94.29	$ 60.55	$ 9.94	$ 332,822
Low N	984	490	255	1730	$ 59.78	$ 15.53	$ 2.53	$ 66,131
Medium N	2457	1239	645	4340	$ 60.05	$ 38.59	$ 6.33	$ 198,996
High N	3920	1992	1037	6948	$ 60.25	$ 61.50	$ 10.13	$ 369,345
Low g	2439	1252	652	4343	$ 20.19	$ 38.24	$ 6.33	$ 112,980
Medium g	2458	1238	644	4341	$ 60.06	$ 38.62	$ 6.33	$ 211,618
High g	2463	1231	641	4334	$ 99.82	$ 38.77	$ 6.32	$ 309,873
Low λ	2437	1249	650	4335	$ 24.20	$ 38.28	$ 6.33	$ 122,606
Medium λ	2457	1239	645	4340	$ 60.06	$ 38.60	$ 6.33	$ 211,486
High λ	2466	1234	642	4343	$ 95.83	$ 38.75	$ 6.33	$ 300,379
Low δ	2454	1256	638	4347	$ 60.02	$ 38.02	$ 4.47	$ 209,890
Medium δ	2453	1240	646	4339	$ 60.03	$ 38.54	$ 6.32	$ 211,483
High δ	2453	1225	653	4332	$ 60.04	$ 39.06	$ 8.18	$ 213,098

* in thousands

Table 3.1.7 – Single purchase experiment results analysis ($\mu = 5$)

Parameter Levels	Z_1/Z	Z_2/Z	Z_3/Z	P_1/P_{Max}	P_2/P_{Max}	P_3/P_{Max}	$Q_1/\sum Q$	$Q_2/\sum Q$	$Q_3/\sum Q$
Low C_D	70%	28%	2%	100%	64%	11%	57%	29%	15%
Medium C_D	70%	28%	2%	100%	64%	11%	57%	29%	15%
High C_D	70%	28%	2%	100%	64%	11%	57%	29%	15%
Low C_P	70%	28%	2%	100%	64%	11%	57%	29%	15%
Medium C_P	70%	28%	2%	100%	64%	11%	57%	29%	15%
High C_P	70%	28%	2%	100%	64%	11%	57%	29%	15%
Low C_S	70%	28%	2%	100%	64%	11%	57%	29%	15%
Medium C_S	70%	28%	2%	100%	64%	11%	57%	29%	15%
High C_S	70%	28%	2%	100%	64%	11%	57%	29%	15%
Low α	70%	28%	2%	100%	64%	11%	57%	29%	15%
Medium α	70%	28%	2%	100%	64%	11%	57%	29%	15%
High α	70%	28%	2%	100%	64%	11%	57%	29%	15%
Low N	88%	11%	1%	100%	26%	4%	57%	28%	15%
Medium N	74%	24%	2%	100%	64%	11%	57%	29%	15%
High N	64%	33%	3%	98%	100%	16%	56%	29%	15%
Low g	43%	52%	4%	53%	100%	17%	56%	29%	15%
Medium g	70%	28%	2%	100%	64%	11%	57%	29%	15%
High g	79%	19%	2%	100%	39%	6%	57%	28%	15%
Low λ	48%	48%	4%	63%	100%	17%	56%	29%	15%
Medium λ	70%	28%	2%	100%	64%	11%	57%	29%	15%
High λ	79%	20%	2%	100%	40%	7%	57%	28%	15%
Low δ	70%	28%	2%	100%	63%	7%	56%	29%	15%
Medium δ	70%	28%	2%	100%	64%	11%	57%	29%	15%
High δ	69%	28%	3%	100%	65%	14%	57%	28%	15%

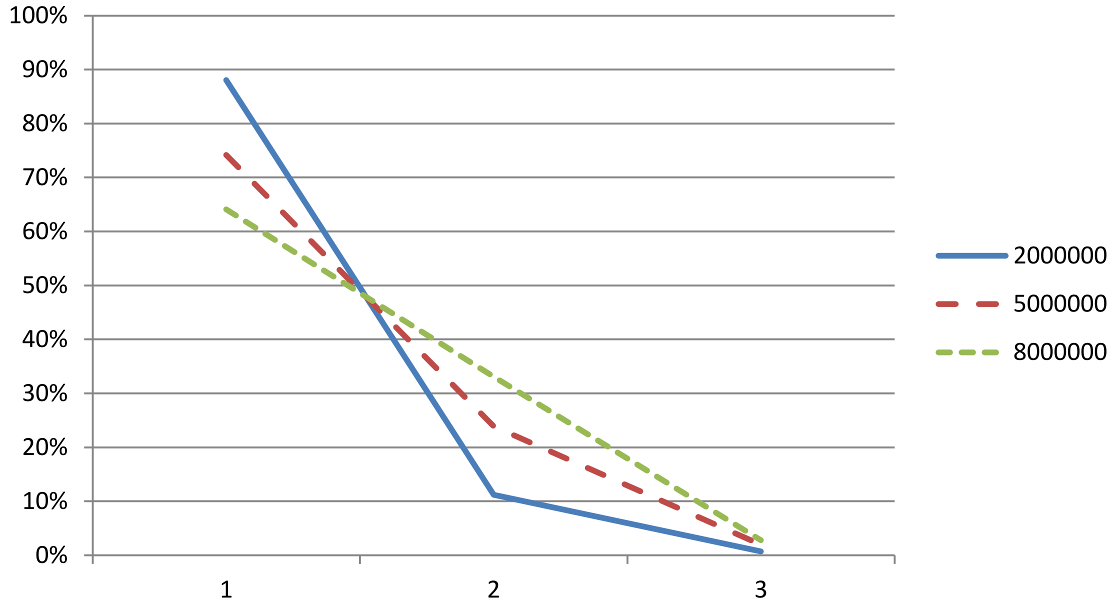

Figure 3.1.19: Single purchase Z_t/Z over time for different market sizes ($\mu = 5$)

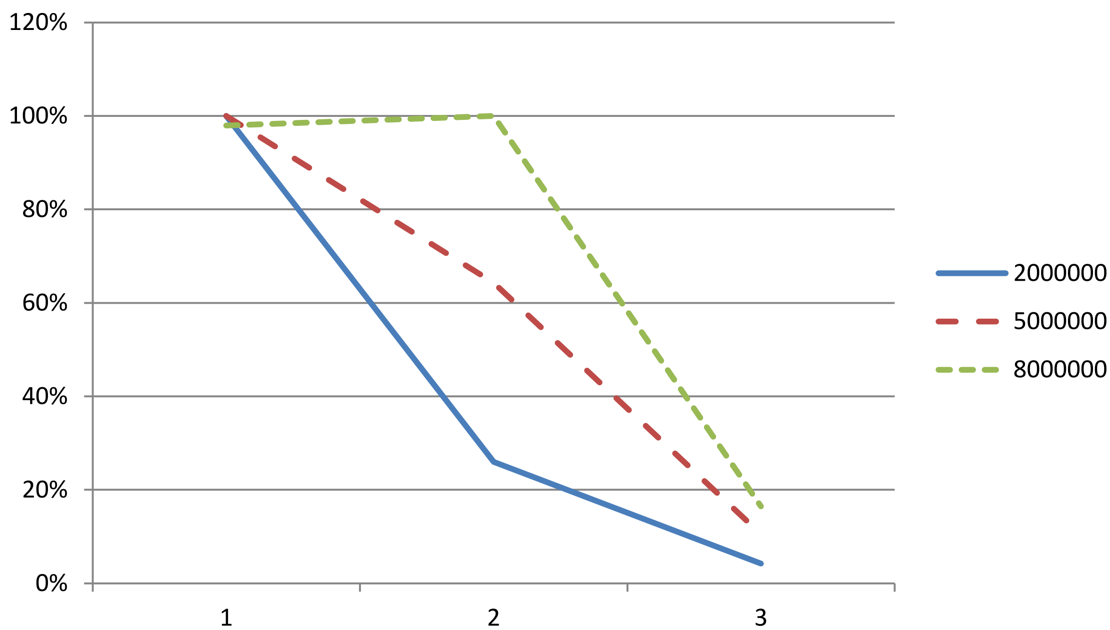

Figure 3.1.20: Single purchase P_t/P_{Max} over time for different market sizes ($\mu = 5$)

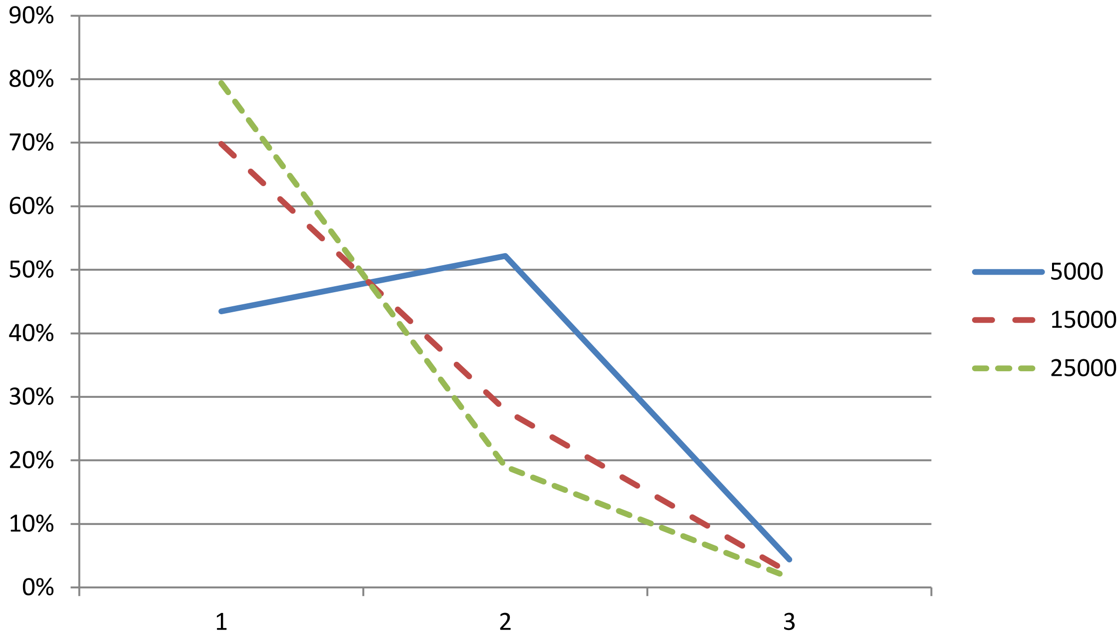

Figure 3.1.21: Single purchase Z_t/Z over time for different g where $\mu = 5$

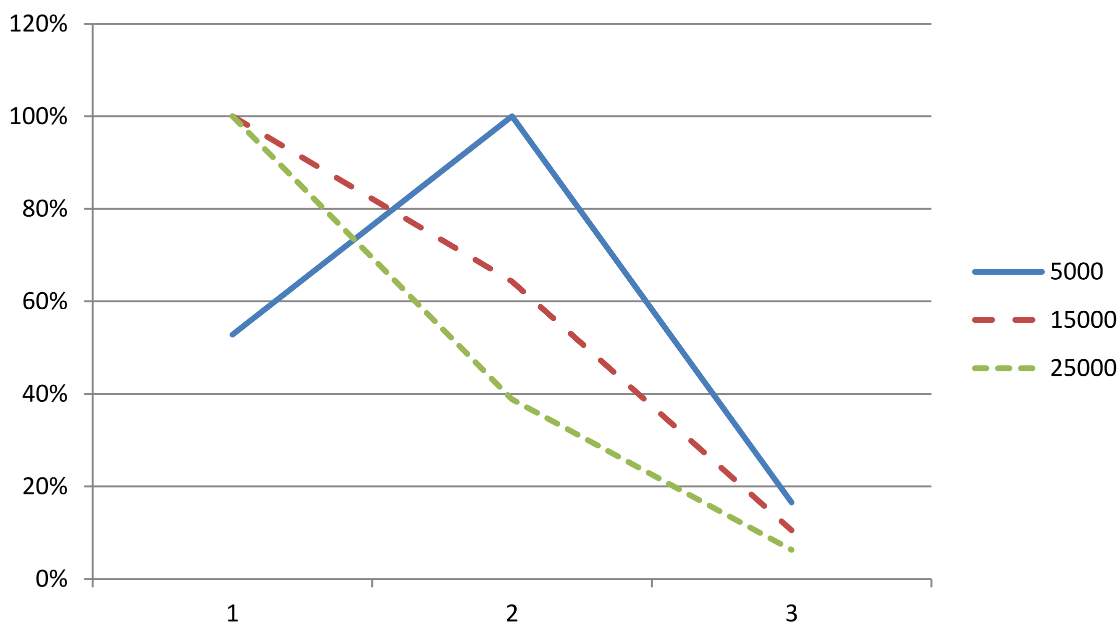

Figure 3.1.22: Single purchase P_t/P_{Max} over time for different g where $\mu = 5$

3.2 Subscription Model

Instead of a single purchase, for this experiment customers decide each period whether or not to purchase a subscription to the game from the publisher. Unlike in the single purchase models where the market size decreases over time as players purchase the game, in the subscription model the market size remains the same as all players must decide whether or not to purchase a subscription. Given these changes, certain parameters (customer growth expectation and customer retention rate) are no longer part of the model. The results of the analysis performed on the parameters in this model are shown in Tables 3.2.2 and 3.2.3.

The results indicate that regardless of parameter examined or parameter level, the game is priced low in the initial period, high in the following period, and low in the final pricing period. For large market sizes the price charged in the initial period and the revenue earned in said period are almost trivially low to the point that the publisher is doing little more than giving the game away. The fact that the market does not completely clear during this initial period is due to the value that some portion of the initial market does not value the game. While the following periods do have decreased sales numbers, the majority of revenue is earned in the period following a low price, see Figures 3.2.1 and 3.2.2. The same phenomena are observed in the effects from varying the beta group test size as shown in Figures 3.2.3 and 3.2.4.

Due to differences in how the utility function is designed between these two models, direct comparison of prices is not possible; however, we can make statements about which is more appropriate under certain conditions based on revenue. Unlike in the single purchase strategy, a customer must decide each period whether or not to buy.

The relationship between prices charged in the single purchase model and the fees charged in the subscription model is outlined in Table 3.2.1. A more detailed analysis of the differences between the price charged and the fees charged is located in Section 5.

Table 3.2.1 – Price vs. fee comparison

Period When Purchased	**Single Purchase Model**	**Subscription Model**
1	P_1	$F_1 + F_2 + F_3$
2	P_2	$F_2 + F_3$
3	P_3	F_3

The subscription model follows the same general patterns established throughout Sections 3.1.1 through 3.1.4 of pricing the game low in the initial period and then higher in the period immediately following in order to capture the benefits of network externalities. The differences in the actual values generated by the experiment are due to the fact that in the subscription model, growth is observed and customer expectations do not matter. This forces the publisher to offer the game at a low price in the initial period for all parameter values unlike the single purchase model in which the publisher will charge a high price in the initial period under certain circumstances. Additionally, the final period price is significantly higher in the subscription model when measured as a percentage of the maximum price charged. This is because, despite the price increase between periods one and two, a significant portion of the potential market does purchase the game in period two because of the impacts of network externalities. A more detailed discussion of these phenomena and their implications can be found in Section 3.5.

Table 3.2.2 – Subscription experiment results

Parameter Levels	n_1*	n_2*	n_3*	$\sum n$*	F_1	F_2	F_3	Z^*
Low C_D	4846	3151	2500	10498	$ 0.24	$ 5.07	$ 4.44	$ 33,664
Medium C_D	4846	3151	2500	10498	$ 0.45	$ 9.51	$ 8.34	$ 63,323
High C_D	4846	3151	2500	10498	$ 0.62	$ 13.03	$ 11.42	$ 86,720
Low C_P	4846	3151	2500	10498	$ 0.44	$ 9.20	$ 8.06	$ 61,355
Medium C_P	4846	3151	2500	10498	$ 0.44	$ 9.20	$ 8.06	$ 61,235
High C_P	4846	3151	2500	10498	$ 0.44	$ 9.20	$ 8.06	$ 61,115
Low C_S	4846	3151	2500	10498	$ 0.34	$ 7.20	$ 6.31	$ 47,828
Medium C_S	4846	3151	2500	10498	$ 0.45	$ 9.36	$ 8.21	$ 62,323
High C_S	4846	3151	2500	10498	$ 0.53	$ 11.05	$ 9.68	$ 73,555
Low α	4846	3151	2500	10498	$ 0.23	$ 4.92	$ 4.31	$ 32,258
Medium α	4846	3151	2500	10498	$ 0.39	$ 8.23	$ 7.21	$ 54,656
High α	4846	3151	2500	10498	$ 0.69	$ 14.46	$ 12.67	$ 96,792
Low N	1716	1303	1000	4019	$ 1.00	$ 3.11	$ 3.33	$ 7,598
Medium N	4852	3148	2500	10500	$ 0.28	$ 9.22	$ 8.06	$ 49,193
High N	7970	5004	4000	16974	$ 0.04	$ 15.28	$ 12.81	$ 126,915
Low g	5000	3125	2500	10625	$ 0.00	$ 9.60	$ 8.00	$ 60,929
Medium g	4878	3146	2500	10524	$ 0.31	$ 9.28	$ 8.05	$ 61,092
High g	4661	3184	2500	10345	$ 1.00	$ 8.73	$ 8.15	$ 61,685
Low λ	4993	3126	2500	10619	$ 0.01	$ 9.58	$ 8.00	$ 60,929
Medium λ	4864	3148	2500	10512	$ 0.34	$ 9.25	$ 8.06	$ 61,108
High λ	4682	3181	2500	10363	$ 0.97	$ 8.78	$ 8.14	$ 61,669

* in thousands

Table 3.2.3 – Subscription experiment results analysis

Parameter Levels	$^{Z_1}/_{Z}$	$^{Z_2}/_{Z}$	$^{Z_3}/_{Z}$	$^{F_1}/_{F_{Max}}$	$^{F_2}/_{F_{Max}}$	$^{F_3}/_{F_{Max}}$	$^{n_1}/_{\sum n}$	$^{n_2}/_{\sum n}$	$^{n_3}/_{\sum n}$
Low C_D	1%	59%	40%	5%	100%	88%	46%	30%	24%
Medium C_D	1%	59%	40%	5%	100%	88%	46%	30%	24%
High C_D	1%	59%	40%	5%	100%	88%	46%	30%	24%
Low C_P	1%	59%	40%	5%	100%	88%	46%	30%	24%
Medium C_P	1%	59%	40%	5%	100%	88%	46%	30%	24%
High C_P	1%	59%	40%	5%	100%	88%	46%	30%	24%
Low C_S	1%	59%	40%	5%	100%	88%	46%	30%	24%
Medium C_S	1%	59%	40%	5%	100%	88%	46%	30%	24%
High C_S	1%	59%	40%	5%	100%	88%	46%	30%	24%
Low α	1%	59%	40%	5%	100%	88%	46%	30%	24%
Medium α	1%	59%	40%	5%	100%	88%	46%	30%	24%
High α	1%	59%	40%	5%	100%	88%	46%	30%	24%
Low N	14%	47%	39%	30%	93%	100%	43%	32%	25%
Medium N	2%	58%	40%	3%	100%	87%	46%	30%	24%
High N	0%	60%	40%	0%	100%	84%	47%	29%	24%
Low g	0%	60%	40%	0%	100%	83%	47%	29%	24%
Medium g	1%	59%	40%	3%	100%	87%	46%	30%	24%
High g	3%	57%	40%	12%	100%	93%	45%	31%	24%
Low λ	0%	60%	40%	0%	100%	84%	47%	29%	24%
Medium λ	1%	59%	40%	4%	100%	87%	46%	30%	24%
High λ	3%	57%	40%	11%	100%	93%	45%	31%	24%

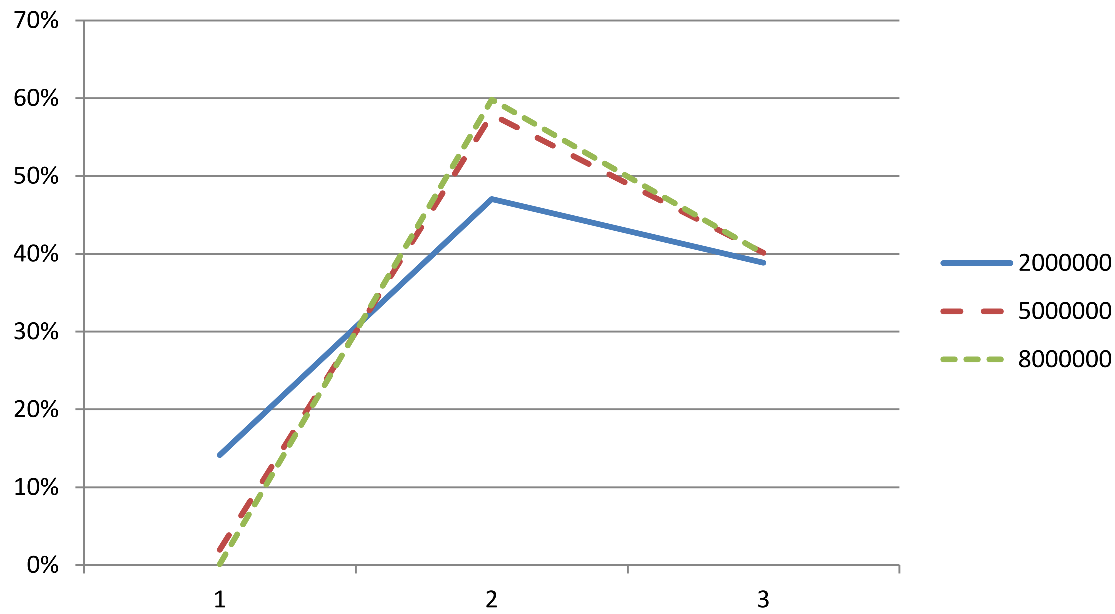

Figure 3.2.1: Subscription Z_t/Z over time for different market sizes

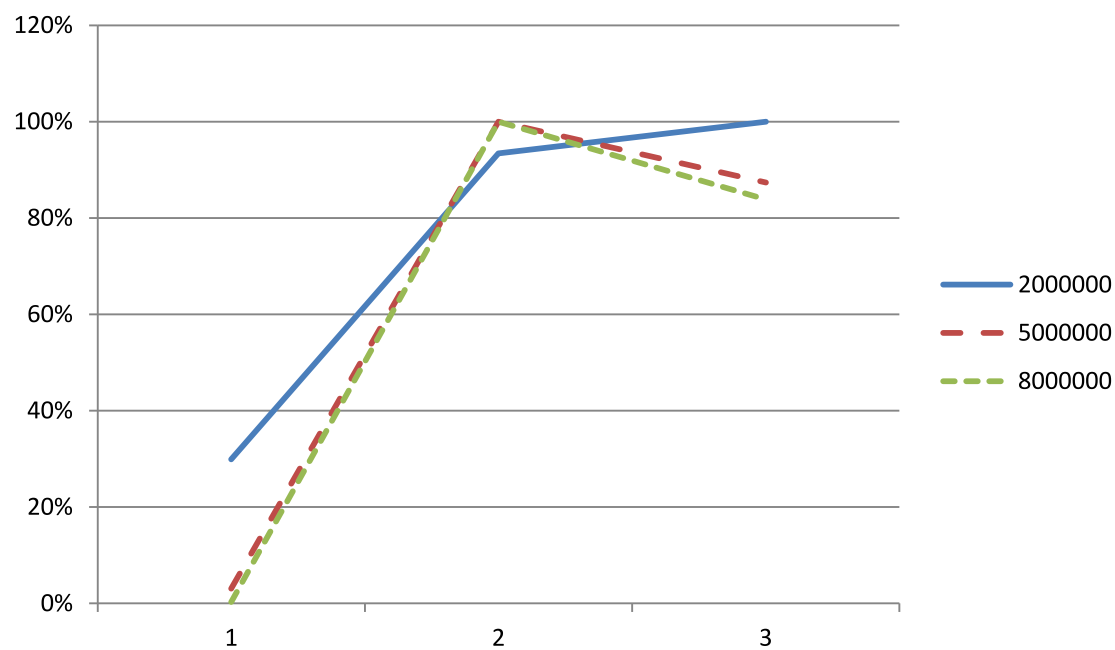

Figure 3.2.2: Subscription F_t/F_{Max} over time for different market sizes

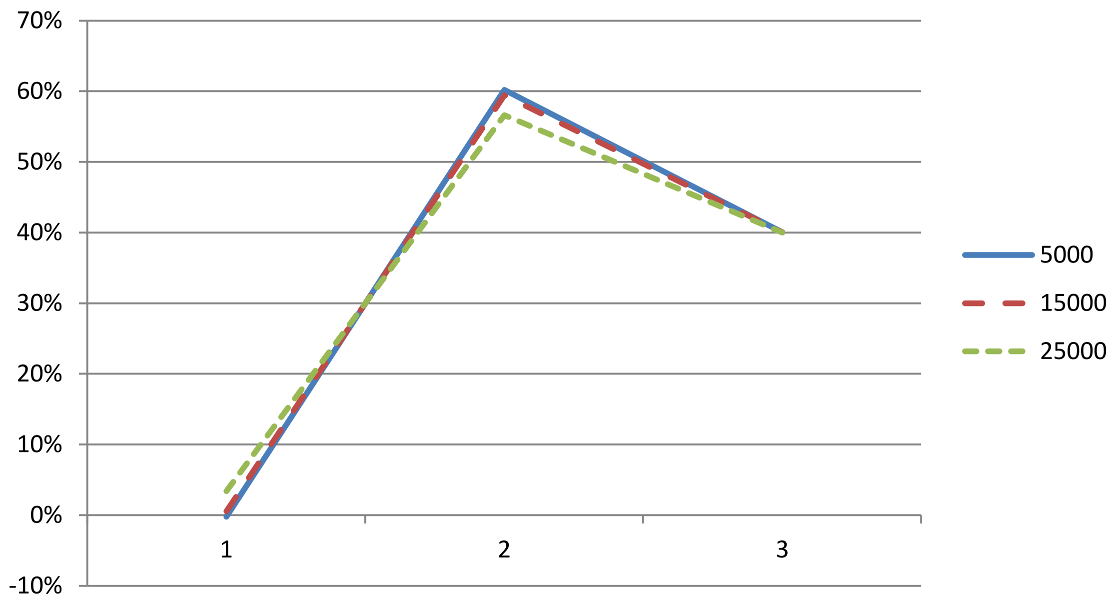

Figure 3.2.3: Subscription Z_t/Z over time for different beta test group sizes

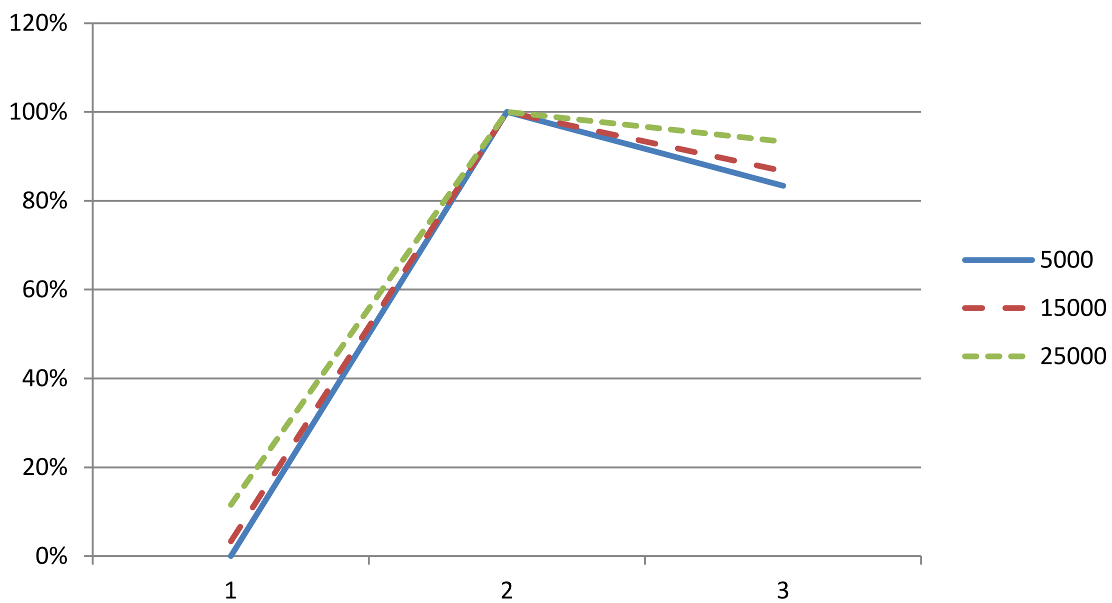

Figure 3.2.4: Subscription F_t/F_{Max} over time for different beta test group sizes

3.3 Five Period Single Purchase Model

The number of price changes was increased from 3 to 5 and we held $\mu = 1$ for this experiment in order to confirm the patterns observed in Section 3.1. This problem was solved using the $NMaximize$ command in Mathematica. While the properties of the problem with $T = 3$ were examined in Proposition 1, we do not provide proof of optimality for $T = 5$. Table 3.3.1 lists the parameters varied in this experiment and their values. Tables 3.3.2 – 3.3.4 show the results of this experiment for prices charged in each period, profits earned in each period, and quantity sold in each period, respectively.

The results for this experiment were similar to those outlined in Section 3.1.1. Generally, the game publisher uses low prices in the first period to stimulate demand and then raises the price in the following period. The prices in subsequent periods are decreasing over time. The same pattern holds for the profits earned in that a majority of the profits are earned in the second period. The same exception holds true in this experiment as in the earlier one for small market sizes. When the market size is small the price is set high initially and then is lowered in subsequent periods with a majority of the profits earned being obtained in the first period. These results are illustrated in Figures 3.3.1 and 3.3.2. All other parameters varied exhibited patterns consistent with the earlier experiment, an example of which can be seen in Figure 3.3.3 for size of the beta group.

Table 3.3.1 – 5 Period single purchase parameter values for numerical experiment

Parameter	Level	Value
C_D	Constant	600,000
C_P	Constant	50,000
C_S	Constant	100,000
α	Constant	0.5
N	Low	2,000,000
	Medium	5,000,000
	High	8,000,000
g	Low	5,000
	Medium	15,000
	High	25,000
λ	Low	20
	Medium	50
	High	80
δ	Low	0.2
	Medium	0.5
	High	0.8

Table 3.3.2 – 5 Period single purchase experiment results analysis for prices

Parameter Levels	P_1/P_{Max}	P_2/P_{Max}	P_3/P_{Max}	P_4/P_{Max}	P_5/P_{Max}
Low N	100%	98%	75%	42%	16%
Medium N	45%	100%	81%	45%	18%
High N	30%	100%	83%	43%	30%
Low g	17%	100%	86%	49%	19%
Medium g	45%	100%	81%	43%	20%
High g	71%	100%	78%	39%	33%
Low λ	20%	100%	85%	43%	37%
Medium λ	45%	100%	81%	43%	20%
High λ	69%	100%	79%	44%	17%
Low δ	48%	100%	63%	25%	8%
Medium δ	45%	100%	81%	41%	18%
High δ	43%	100%	98%	63%	45%

Table 3.3.3 – 5 Period single purchase experiment results analysis for profit

Parameter Levels	Z_1/Z	Z_2/Z	Z_3/Z	Z_4/Z	Z_5/Z
Low $\boldsymbol{N}$	56%	28%	12%	3%	0%
Medium $\boldsymbol{N}$	32%	41%	20%	6%	1%
High $\boldsymbol{N}$	22%	46%	23%	7%	1%
Low $\boldsymbol{g}$	11%	52%	27%	9%	2%
Medium $\boldsymbol{g}$	27%	44%	21%	6%	1%
High $\boldsymbol{g}$	39%	38%	17%	5%	1%
Low $\boldsymbol{\lambda}$	13%	52%	26%	8%	1%
Medium $\boldsymbol{\lambda}$	27%	44%	21%	6%	1%
High $\boldsymbol{\lambda}$	38%	38%	18%	6%	1%
Low $\boldsymbol{\delta}$	30%	49%	17%	4%	0%
Medium $\boldsymbol{\delta}$	28%	44%	21%	6%	1%
High $\boldsymbol{\delta}$	25%	39%	25%	9%	2%

Table 3.3.4 – 5 Period single purchase experiment results analysis for quantity sold

Parameter Levels	$Q_1/\sum Q$	$Q_2/\sum Q$	$Q_3/\sum Q$	$Q_4/\sum Q$	$Q_5/\sum Q$
Low $\boldsymbol{N}$	46%	25%	15%	9%	5%
Medium $\boldsymbol{N}$	43%	27%	16%	9%	5%
High $\boldsymbol{N}$	42%	27%	16%	10%	5%
Low $\boldsymbol{g}$	41%	28%	17%	10%	5%
Medium $\boldsymbol{g}$	44%	27%	16%	9%	5%
High $\boldsymbol{g}$	45%	26%	15%	9%	4%
Low $\boldsymbol{\lambda}$	41%	28%	16%	10%	5%
Medium $\boldsymbol{\lambda}$	43%	27%	16%	9%	5%
High $\boldsymbol{\lambda}$	45%	26%	15%	9%	5%
Low $\boldsymbol{\delta}$	43%	28%	16%	9%	4%
Medium $\boldsymbol{\delta}$	43%	27%	16%	9%	5%
High $\boldsymbol{\delta}$	43%	25%	16%	10%	6%

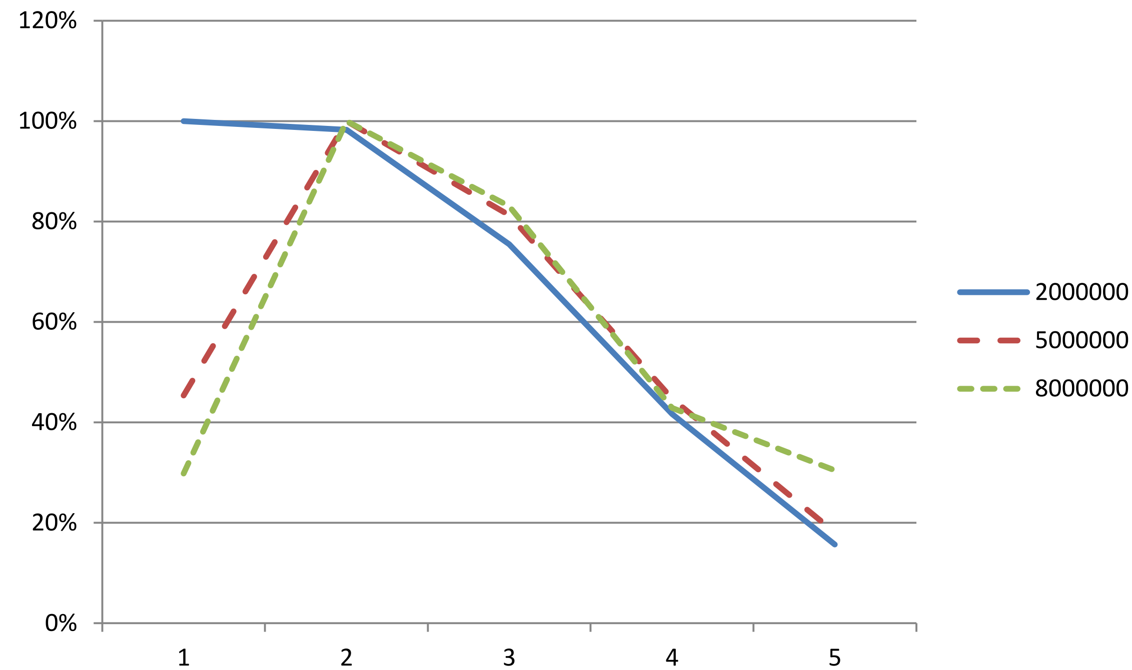

Figure 3.3.1: 5 Period single purchase P_t/P_{Max} over time for different market sizes

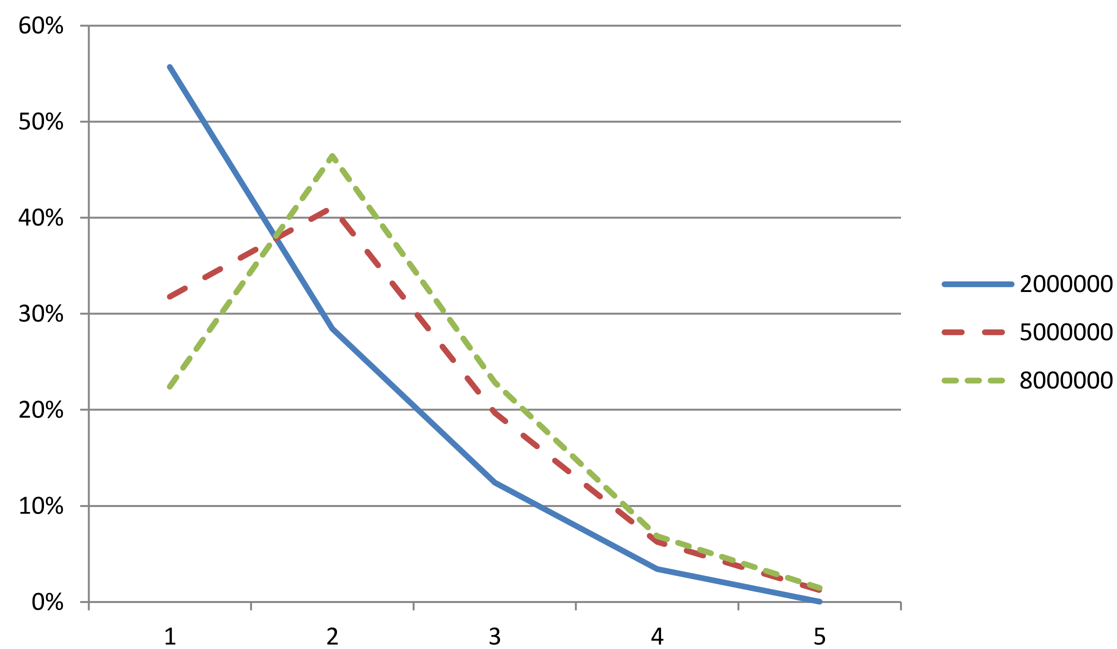

Figure 3.3.2: 5 Period single purchase Z_t/Z over time for different market sizes

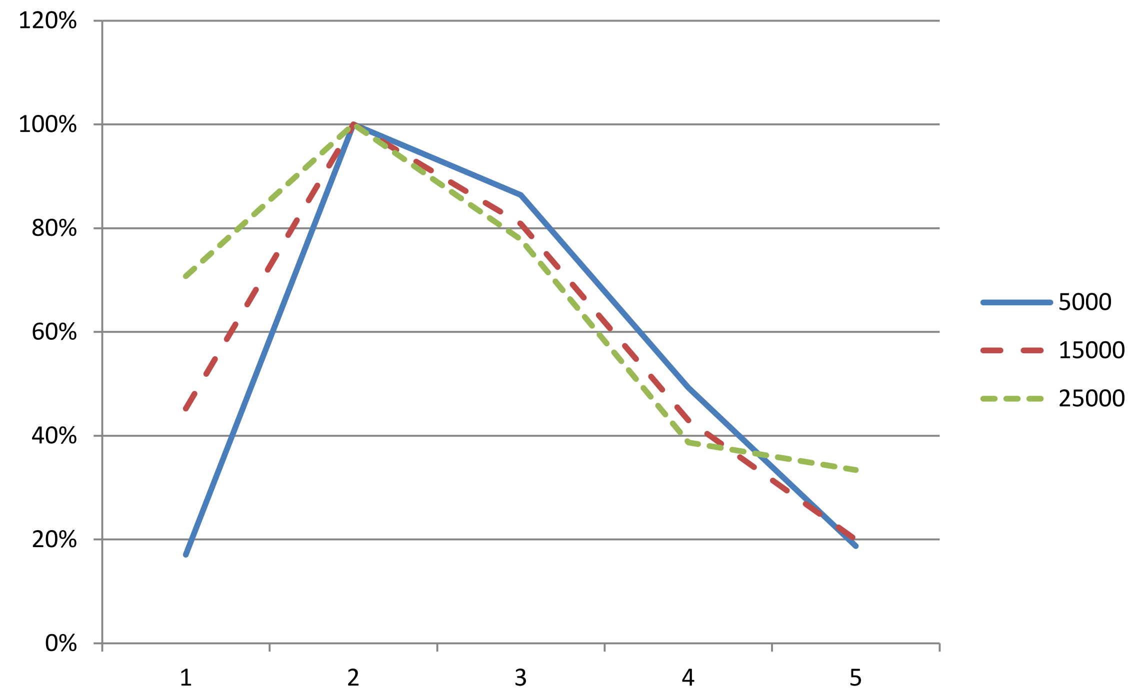

Figure 3.3.3: 5 Period single purchase P_t/P_{Max} over time for different g

3.4 Five Period Subscription Model

As in Section 3.3, the number of price changes was increased from 3 to 5 for this experiment in order to confirm the patterns observed in Section 3.2. Tables 3.4.1 – 3.4.3 show the analysis of the results of this experiment for prices charged in each period, profits earned in each period, and quantity sold in each period, respectively.

The results of this model show an interesting pattern in the prices set by the publisher. The publisher begins with a low price to increase sales and follows this with a price increase to capitalize on the effects of network externalities. In the following two periods, the price is lowered to again increase sales. In the final period, the publisher raises the price to again capitalize on the effects of network externalities, see Figures 3.4.2 – 3.4.3. This price oscillation (low, high, low, high) occurs when the publisher chooses to change prices for the game more than three times over the life cycle of the product. With the subscription model, the importance of network externalities dominates all of the parameters tested without the same exceptions noted in Sections 3.1 and 3.3.

Table 3.4.1 – 5 Period subscription experiment results analysis for prices

Parameter Levels	F_1/F_{Max}	F_2/F_{Max}	F_3/F_{Max}	F_4/F_{Max}	F_5/F_{Max}
Low $\boldsymbol{N}$	28%	93%	61%	61%	100%
Medium $\boldsymbol{N}$	3%	100%	53%	56%	91%
High $\boldsymbol{N}$	0%	100%	51%	55%	88%
Low $\boldsymbol{g}$	0%	100%	50%	55%	88%
Medium $\boldsymbol{g}$	3%	100%	52%	56%	90%
High $\boldsymbol{g}$	11%	100%	56%	59%	96%
Low $\boldsymbol{\lambda}$	0%	100%	50%	55%	88%
Medium $\boldsymbol{\lambda}$	3%	100%	53%	56%	91%
High $\boldsymbol{\lambda}$	10%	100%	56%	59%	95%

Table 3.4.2 – 5 Period subscription experiment results analysis for profit

Parameter Levels	Z_1/Z	Z_2/Z	Z_3/Z	Z_4/Z	Z_5/Z
Low $\boldsymbol{N}$	8%	28%	19%	20%	24%
Medium $\boldsymbol{N}$	1%	34%	19%	21%	25%
High $\boldsymbol{N}$	0%	35%	19%	21%	25%
Low $\boldsymbol{g}$	0%	35%	19%	21%	25%
Medium $\boldsymbol{g}$	0%	34%	19%	21%	25%
High $\boldsymbol{g}$	2%	33%	19%	21%	25%
Low $\boldsymbol{\lambda}$	0%	35%	19%	21%	25%
Medium $\boldsymbol{\lambda}$	0%	34%	19%	21%	25%
High $\boldsymbol{\lambda}$	2%	33%	19%	21%	25%

Table 3.4.3 – 5 Period subscription experiment results analysis for quantity sold

Parameter Levels	$n_1/\sum n$	$n_2/\sum n$	$n_3/\sum n$	$n_4/\sum n$	$n_5/\sum n$
Low $\boldsymbol{N}$	26%	19%	20%	20%	15%
Medium $\boldsymbol{N}$	28%	18%	20%	20%	15%
High $\boldsymbol{N}$	29%	18%	20%	20%	14%
Low $\boldsymbol{g}$	29%	18%	20%	20%	14%
Medium $\boldsymbol{g}$	28%	18%	20%	20%	14%
High $\boldsymbol{g}$	27%	18%	20%	20%	15%
Low $\boldsymbol{\lambda}$	29%	18%	20%	20%	14%
Medium $\boldsymbol{\lambda}$	28%	18%	20%	20%	14%
High $\boldsymbol{\lambda}$	27%	18%	20%	20%	15%

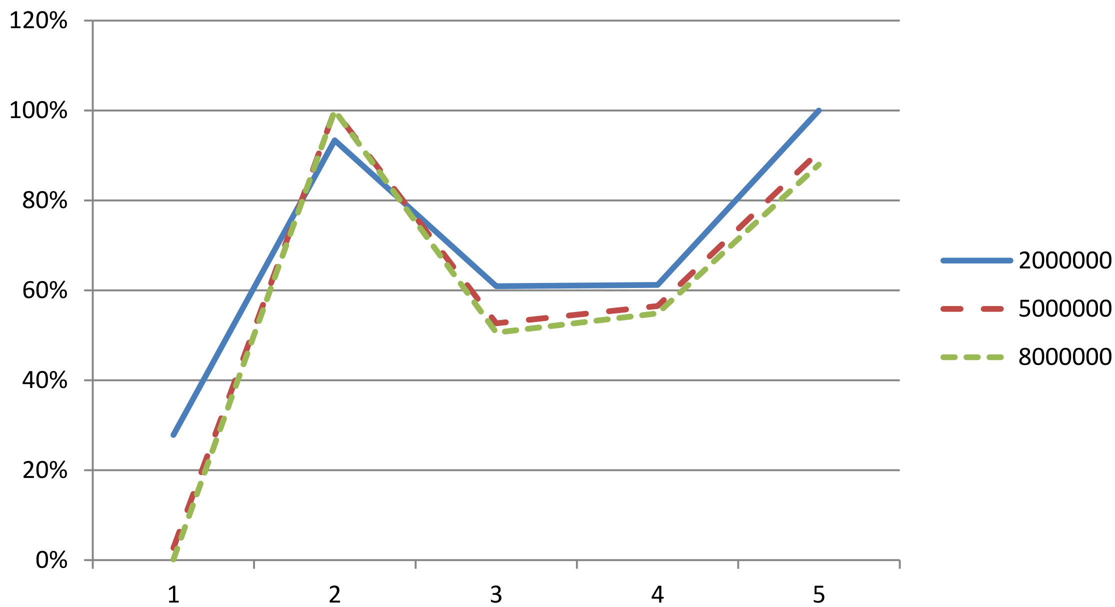

Figure 3.4.1: 5 Period subscription F_t/F_{Max} over time for different market sizes

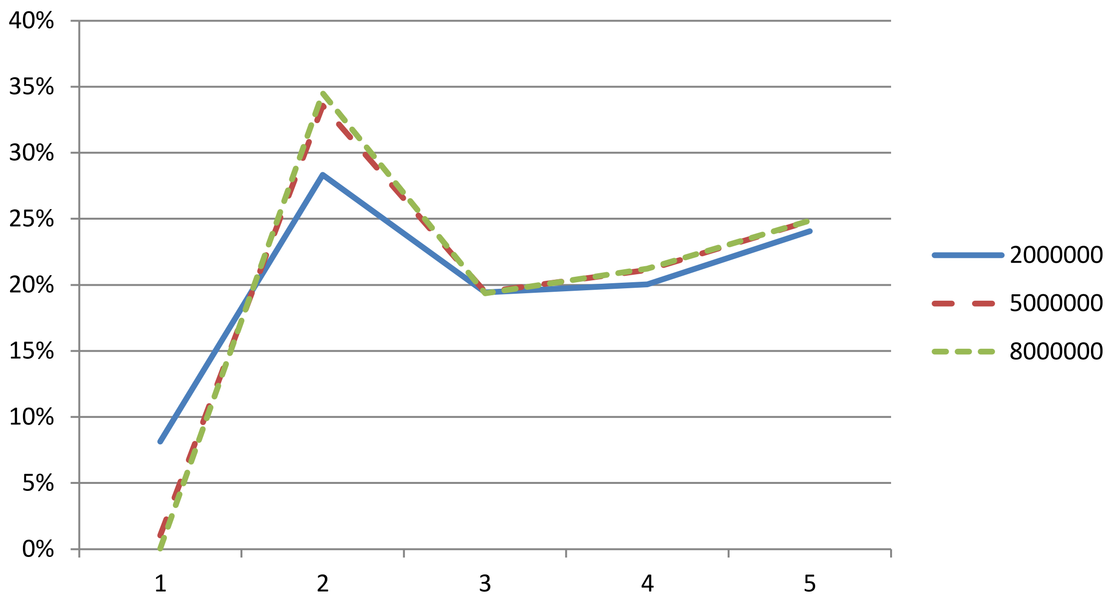

Figure 3.4.2: 5 Period subscription Z_t/Z over time (T) for different market sizes

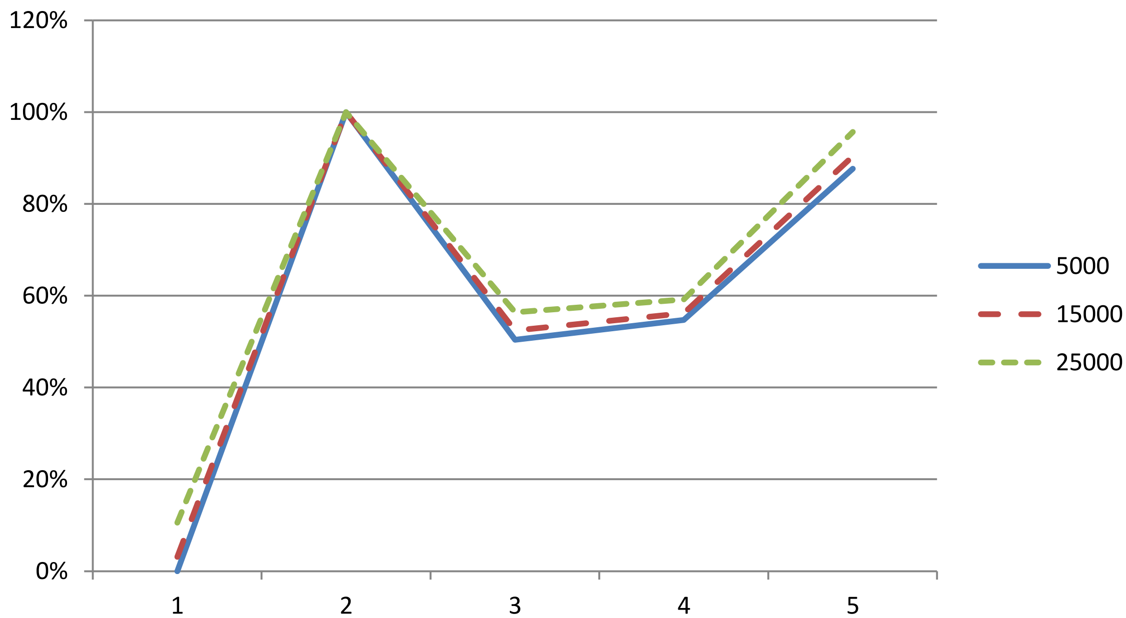

Figure 3.4.3: 5 Period subscription Ft/FMax over T for different beta test group sizes

3.5 Model Comparisons

Comparisons of model performance are outlined in Table 3.5.1 and 3.5.2 for several three period experiments. While comparisons of prices or quantity sold between model types is not possible, we can compare the revenues earned in each and for each period. Respectively, these tables show the differences between the single purchase model with no customer growth and the subscription model and between the single purchase model with moderate customer growth and the subscription model again. Tables 3.5.3 and 3.5.4 show the percent change in profit of these differences. Table 3.5.5 provides a comparison between the prices charged in the different single purchase experiments and the subscription fees charged. We note the following observations about the performance of these three models:

- For products that exhibit network externalities, the size of the market is the most important of all the environmental characteristics
- When there is no (or very little) customer growth expectation, the publisher should follow subscription pricing as this model provides superior profit levels except when the potential market size is small
- Beyond a certain threshold of customer growth expectation, the publisher should follow a single purchase pricing strategy
- If the customers believe that growth will be low and the publisher believes that the customers are wrong and that growth expectation is higher or will change, a subscription pricing strategy will provide more profit than a single purchase model

- If a subscription model is determined to be the strategy that best maximizes profit for the publisher, the publisher should oscillate prices to capitalize on network externalities
- If the publisher is cash-starved or short term cash flow is a concern, the publisher should follow a single purchase pricing model as this provides the greatest amount of revenue early in the game's lifecycle
- If the publisher feels uncertain about the long term prospects of the company with respect to survival (i.e. the company may cease to exist for reasons not related to the game being offered), the publisher should follow a single purchase pricing strategy regardless of customer growth expectation as this strategy provides the maximum amount of profit earned in the first pricing period due to the fact that customers who purchase during the initial period expect to be able to play the game for several additional periods

It should be noted that this last point should be considered a "Nuclear Option" in that if a company promises to provide a gaming environment for a certain amount of time, the customers will expect the publisher to do just that. It would be expected that the pre-release market perception coefficient (λ) would be significantly impacted for subsequent offerings in a negative way should the publisher choose to follow this action prematurely.

Since the experiments in this chapter were conducted with a discount rate of zero, we anticipate that raising the discount rate will result in a reduced performance by the subscription model. Specifically, we expect Tables 3.5.4 and 3.5.5 to show slightly different results with the presence of discounting.

Table 3.5.1 – Differences between $\mu = 1$ single purchase and subscription models

Parameter Levels	$Z_1^P - Z_1^F$	$Z_2^P - Z_2^F$	$Z_3^P - Z_3^F$	$Z^P - Z^F$
Low N	$ 4,384.73	$ (1,481.79)	$ (2,647.91)	$ 255.42
Medium N	$ 13,154.96	$ (13,178.90)	$ (15,733.92)	$ (15,757.50)
High N	$ 22,560.67	$ (36,042.87)	$ (39,812.15)	$ (53,294.22)
Low g	$ 4,750.23	$ (17,650.06)	$ (19,177.16)	$ (32,076.55)
Medium g	$ 13,809.39	$ (17,229.35)	$ (19,365.15)	$ (22,785.43)
High g	$ 21,540.74	$ (15,824.15)	$ (19,651.67)	$ (13,935.32)
Low λ	$ 5,669.63	$ (17,649.53)	$ (19,203.95)	$ (31,184.15)
Medium λ	$ 13,709.35	$ (17,148.80)	$ (19,372.54)	$ (22,812.09)
High λ	$ 20,721.38	$ (15,905.23)	$ (19,617.49)	$ (14,801.06)
in thousands				

Table 3.5.2 – Differences between $\mu = 3$ single purchase and subscription models

Parameter Levels	$Z_1^P - Z_1^F$	$Z_2^P - Z_2^F$	$Z_3^P - Z_3^F$	$Z^P - Z^F$
Low N	$ 23,396.33	$ 1,068.01	$ (2,678.77)	$ 21,785.57
Medium N	$ 60,977.13	$ 2,859.91	$ (15,977.79)	$ 47,859.25
High N	$ 99,199.19	$ 5,103.01	$ (40,490.58)	$ 63,811.62
Low g	$ 20,741.08	$ 2,329.96	$ (19,537.96)	$ 3,533.09
Medium g	$ 61,680.19	$ 2,676.12	$ (19,678.91)	$ 44,677.40
High g	$ 101,151.39	$ 4,024.85	$ (19,930.28)	$ 85,245.96
Low λ	$ 24,803.30	$ 2,293.05	$ (19,559.60)	$ 7,536.75
Medium λ	$ 61,536.66	$ 2,757.82	$ (19,686.92)	$ 44,607.55
High λ	$ 97,232.70	$ 3,980.07	$ (19,900.64)	$ 81,312.13
in thousands				

Table 3.5.3 – Percent change in profit between $\mu = 1$ single purchase vs. subscription

Parameter Levels	$\frac{Z_1^P - Z_1^F}{Z_1^F}$	$\frac{Z_2^P - Z_2^F}{Z_2^F}$	$\frac{Z_3^P - Z_3^F}{Z_3^F}$	$\frac{Z^P - Z^F}{Z^F}$
Low $\boldsymbol{N}$	378%	-38%	-83%	3%
Medium $\boldsymbol{N}$	1340%	-46%	-79%	-32%
High $\boldsymbol{N}$	15647%	-47%	-78%	-42%
Low $\boldsymbol{g}$	-3167%	-48%	-78%	-53%
Medium $\boldsymbol{g}$	4246%	-47%	-78%	-37%
High $\boldsymbol{g}$	1021%	-45%	-79%	-23%
Low $\boldsymbol{\lambda}$	-4308%	-48%	-78%	-51%
Medium $\boldsymbol{\lambda}$	3310%	-47%	-78%	-37%
High $\boldsymbol{\lambda}$	1035%	-45%	-79%	-24%

Table 3.5.4 – Percent change in profit between $\mu = 3$ single purchase vs. subscription

Parameter Levels	$\frac{Z_1^P - Z_1^F}{Z_1^F}$	$\frac{Z_2^P - Z_2^F}{Z_2^F}$	$\frac{Z_3^P - Z_3^F}{Z_3^F}$	$\frac{Z^P - Z^F}{Z^F}$
Low $\boldsymbol{N}$	2019%	28%	-84%	287%
Medium $\boldsymbol{N}$	6211%	10%	-80%	97%
High $\boldsymbol{N}$	68799%	7%	-79%	50%
Low $\boldsymbol{g}$	-13827%	6%	-79%	6%
Medium $\boldsymbol{g}$	18964%	7%	-80%	73%
High $\boldsymbol{g}$	4795%	11%	-80%	138%
Low $\boldsymbol{\lambda}$	-18846%	6%	-79%	12%
Medium $\boldsymbol{\lambda}$	14858%	8%	-80%	73%
High $\boldsymbol{\lambda}$	4856%	11%	-80%	132%

Table 3.5.5 – Price vs. subscription fee analysis

	$\mu = 1$			$\mu = 3$		
Parameter Levels	$\frac{P_1}{F_1 + F_2 + F_3}$	$\frac{P_2}{F_2 + F_3}$	$\frac{P_3}{F_3}$	$\frac{P_1}{F_1 + F_2 + F_3}$	$\frac{P_2}{F_2 + F_3}$	$\frac{P_3}{F_3}$
Low N	0.80	0.80	0.74	3.39	1.61	0.75
Medium N	0.35	0.72	0.77	1.45	1.48	0.78
High N	0.22	0.70	0.78	0.91	1.45	0.79
Low g	0.12	0.69	0.78	0.49	1.44	0.79
Medium g	0.35	0.72	0.77	1.44	1.48	0.78
High g	0.56	0.75	0.76	2.36	1.53	0.77
Low λ	0.14	0.69	0.78	0.59	1.44	0.79
Medium λ	0.34	0.72	0.77	1.44	1.48	0.78
High λ	0.54	0.75	0.76	2.26	1.52	0.77

CHAPTER 4: SIMULATION

4.1 Complex Adaptive Systems & Agent Based Modeling

In this section of the paper, we propose the use of simulation tools in order to gain insight into the complex phenomena described in the earlier chapters. Following a description of Complex Adaptive Systems and Agent Based Modeling simulations we present a discussion about the appropriateness of such systems for this type of research and the suitability of simulation tools in general for use in examining problems of the type detailed earlier. We will then move into a discussion about the simulation system used in this study and its assumptions as well as provide a description of the overall design and operability of the simulation. Finally, we conclude with a discussion of the results and implications of this experiment.

4.1.1 Introduction to CAS & ABM

Complex Adaptive Systems (CAS) are a methodology for studying interrelated and complicated problems that do not lend themselves well to traditional empirical or mathematical models. While CAS has been used to describe phenomena in the fields of physics, ecology, and weather systems, (Brownlee, 2007) it has also been used less often but also in the fields of business and economics. Agent Based Modeling (ABM) has been used in CAS-based business research to describe pricing behaviors and corresponding consumer behaviors under a variety of complex conditions. Of particular note is economic research done in the field of pricing under piracy. ABM based research on pricing in the face of piracy reveals that piracy reduces the effectiveness of skimming strategies and that the success of any skimming strategy is dependent on the firms' abilities to affect the piracy risk cost faced by consumers (Khouja, Hadzikadic, Rajagopalan, & Tsay, 2008). Given the complicated inter-dependencies of this model, an analysis of this type would be more difficult if analytical modeling was used.

An advantage of CAS and ABM in particular over other research methodologies is their ability to model more complex relationships than would otherwise be possible. As agents act in accordance to their rules, their behavior, given the differences in their individual parameters and their interactions with other agents, taken in aggregate allows conclusions to be made about the system behavior. For example, a particular group of agents may typically behave a particular way when confronted with a certain combination of environmental factors along with actions from one or more other group of agents. This type of insight is not possible in most empirical research due to the exorbitant data collection requirements and the difficulty therein. While we are able to track the behaviors of the individual agents or actors in the simulation, this aggregation is where the research effort gains a significant portion of its value: though its ability to predict individual behavior based on the behavior of a collection of behaviors given a certain set of conditions.

As with any type of simulation, a key goal of the simulation study is to evaluate how the model moves towards steady-state equilibrium. As the system moves towards this equilibrium, it is possible to study snapshots at individual points in time; however, it is typically of greater value to view the general trends that lead agents towards equilibrium. These trends may come from a variety of class or environmental factors and their complex interactions with the simpler rules that agents are programmed to follow. Agents need not be complex; indeed simpler rules are generally more effective when the system is viewed as a whole (Innes, 1999).

4.1.2 Suitability of CAS & ABM

Given the complex and interrelated nature of the multiplayer online game phenomena, it is wise to consider the use of simulation (Law, 2007) in studying this problem. Further, given that the problem as presented is non-linear and involves several parties whose utility is dependent upon the actions of numerous other parties (i.e. via network externalities), CAS and specifically ABM are suitable means for further investigation. Given that agents will behave in an autonomous manner and will be making decisions based on the rules of their class, we expect to be able to point to certain generalized rules or circumstances that hold for the different classes of agents. CAS has been used to explain phenomena related to markets that contain certain unquantifiable externalities such as heroin dealing based on limited datasets (Hoffner, Bobashev, & Morris, 2009). A particular convenience in the aforementioned research effort is that normal economic rules can be suspended or modified such as easing rational behavior rules given that the behavior in question involves a highly addictive substance. This is particularly of interest given the network externalities that exist in multiplayer online games. Since such systems are self-organizing and are focused at the micro-level rules as they constrain behavior within a dynamic environment, it is possible to see how decentralized group (or class) decisions evolve and are collectively made over time without any overt efforts to control the collective behavior by any one member of the common class. Again, given the network externalities inherent in our problem, this mass movement is of particular interest. Also, not all relationships within the CAS are important which means that with time the important behaviors of the system will rise to the surface and the system will achieve some form of long-term repetitive pattern or will otherwise achieve some form of steady-state.

The following sections present an agent based modeling simulation for testing several different pricing models. This simulation was conducted to explore the impacts of network externalities on the pricing of online multiplayer video games. Following sections present a discussion about the agents, their rules, the simulation procedures, and finally, the results and conclusions drawn from this study.

4.2 Simulation Design

This simulation was performed in the NetLogo simulation environment. The user inputs a variety of parameters and several sets of agents follow their rules as outlined in the following sections. There are two types of agents, consumers and the game publisher. In this experiment, there are two pricing models (subscription and single purchase) both of which have four pricing strategies: fixed price (FP), revenue seeking (RS), low-high-low oscillation (O1), and high-low-high oscillation (O2). The parameters used by the simulation are shown in Table 4.1.1. The following sections detail a revenue dependent subscription pricing scheme with several additional schemes and modifications provided before a description of the simulation's procedures.

Table 4.1.1 – Simulation parameters

Simulation Name	Description	Notation	Notes
N	Number of consumers in the simulation	N	3
Active_Players	Number of players playing the game in period t	Y_t	1
#_Player_Links	Number of connections between consumer i and other consumers	L_i	
Mean_Player_Links	Mean value of L_i	L_P	3
Player_Link_StDev	Standard deviation of L_i	σ_L	3
Fellow_Gamers	Number of neighbors of consumer i playing the game in period t	$G_{i,t}$	1
Joining_Probability	Probability of consumer i joining game in period t	$p_{i,t}$	1
#_Game_Links	Number of beginning links originating from the game publisher to a randomly selected consumers	n_0	3
Network_Externalities	Effects of network externalities	y	3
Player_Budget	Budget of consumer i discounted in period t	$B_{i,t}$	1
Income	Undiscounted budget of consumer i	b_i	
Mean_Budget	Mean value of B_i	μ_B	3
Budget_StDev	Standard deviation of B_i	σ_B	3
Price	Price charged by game publisher during in period t	P_t	1, 3 (for P_1)
Price_Change	Price change (up or down) that the game publisher enacts in period $t+1$ from period t	ΔP_t	3
Retention_Rate	$(1-\delta)$ is the probability that a player will quit playing the game during any given period t	δ	2, 3
Discount	Consumer discount rate	φ	3
IRR_Publisher	Internal Rate of Return for publisher	r	3
Duration	Time horizon	T	3
Periods_Discounted	Number of periods that budget is discounted	H	2, 3

Notes
1) Varies with t
2) Single Purchase only
3) User specified

4.2.1 Agents

4.2.1.1 Consumers

A few basic rules govern whether or not a consumer chooses to purchase the game. First, if a consumer has a neighbor that is playing the game, the player has a nonzero probability of subscribing to the game. This probability increases with the number of neighbors that are playing according to the function:

$$p_{i,t} = \left(\frac{G_{i,t}}{L_i}\right)^{Y} \qquad [4.1]$$

Where $0 < Y < 1$ is the effect of network externalities and where $G_{i,t}$ is the number of neighbors of consumer i who are playing the game in period t. This function results in a non-linear relationship between the neighbors who are fellow gamers and the probability of player i with L_i neighbors joining the game as shown in Figure 1.1. With zero neighbors playing a game, there is no chance of a consumer choosing to subscribe to the game. With a single neighbor playing out of a total of 10 neighbors, the probability increases to 32%, assuming the consumer's budget is greater than or equal to the price, and with five neighbors playing the probability of joining the game increases to approximately 71%. If all of the consumer's neighbors are active in the game, the probability of joining increases to 100%. If the total number of neighbors is less (i.e. two neighbors) then if one neighbor is playing there is now a 71% chance of the consumer choosing to buy a subscription and 100% chance if both neighbors are playing. Another function which increases the variability of the purchasing decision (i.e. $Max\ p_{i,t} = 0.50$) is:

$$p_{i,t} = 1 - \frac{1}{\frac{G_{i,t}}{L_i} + 1} \qquad [4.2]$$

Assuming the consumer is aware of the game (i.e. $p_{i,t} > 0$) then the player will evaluate the game's price in terms of their budget. If the game is within the consumer's budget, the consumer will purchase the game. The consumer's budget (b_i) is a normally distributed random variable with a mean of μ_B and a standard deviation of σ_B. Once generated, a player's budget does not change from period to period. A Player will leave a game if it is priced outside their budget but remain aware of the game as discussed in subsequent sections. These players have the option of rejoining the game if the price of the game falls to within their budget. The mechanics of the process in which consumers decide whether or not to buy the game are explained greater detail in Section 4.2.2.2. Each consumer has a budget of b_i that is normally distributed according to the parameters above. To enable comparisons between subscription and single purchase models, the budget per period of the single purchase strategies are discounted at the discount rate φ such that:

$$B_i = \sum_{t=0}^{T} \frac{b_i}{\left(1 - \frac{\varphi}{12}\right)^t} \qquad [4.3]$$

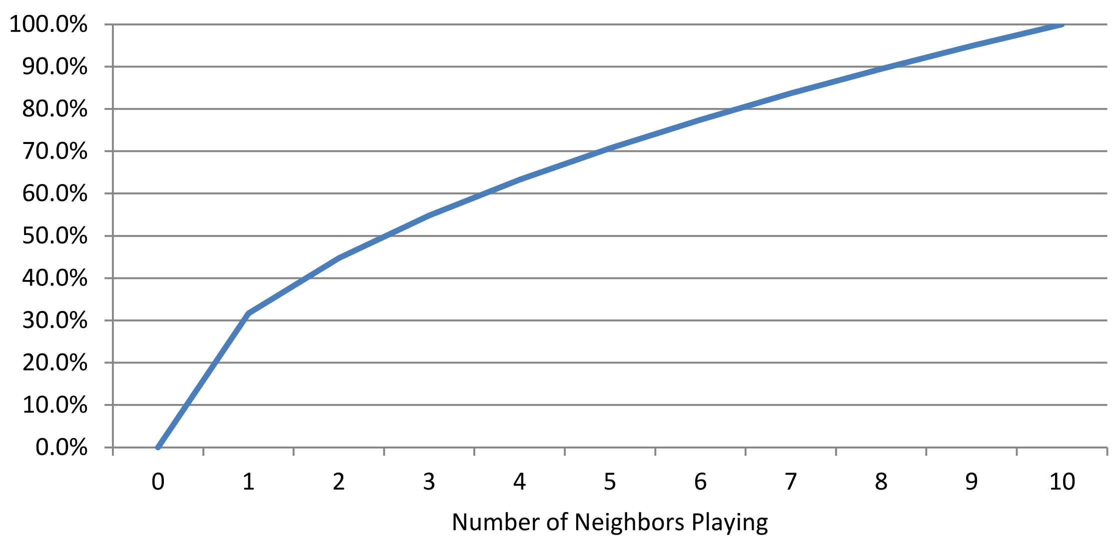

Figure 4.1.1: Probability of a consumer joining a game ($L_i = 10, Y = 0.5$)

4.2.1.2 Game Publisher

Like consumers, the game publisher follows a few rules. At the end of each period, the game publisher has the option of changing the price. The simulation has a selection menu which allows the examination of different pricing strategies. With this feature, the user has the option of selecting the rules that the game publisher will follow from the following:

Rule 1: Revenue seeking (RS). If revenue increased between the last period and the current period, the publisher will increase price by an amount specified by the user (ΔP_t or ΔF_t). If revenue decreased between the last period and the current period, the publisher will decrease price by the same amount. In this policy, the simulation needs to identify the optimal initial price (P_1 or F_1) and the optimal change amount, (ΔP_t or ΔF_t).

Rule 2: Fixed price (FP). The user can select a fixed price for the entire life of the game. In this mode, the game publisher will not deviate from the user specified P_1 or F_1regardless of the changes in revenue. So for this policy, the simulation needs to identify the optimal price (P_1 or F_1) to charge for the entire horizon.

Rule 3: Oscillation (O1 or O2). The user can also choose to change the pricing model option which will force the game into oscillating price in a low, high, low, high… pattern. The aforementioned ΔP_t or ΔF_t parameter represents the represents the difference between the high and low values of the oscillation pattern. For this policy, the simulation needs to identify the optimal initial price (P_1 or F_1) the optimal change amount (ΔP_t or ΔF_t) and the direction of the first change.

Rule 4: When the single purchase selection is activated, players purchase the game only once. Once a player has purchased the game, they have the same awareness of the game even if they choose to quit playing for some time as a direct link to the game is maintained. They may choose to rejoin if enough neighbors are playing the game with their budget not being a consideration as the simulation is operating in single purchase mode and they already own the rights to play the game. The single purchase model option enables the user to enter a value for retention rate δ where $1 - \delta$ is the probability each period that a player who has purchased the game will stop playing until reactivated by the simulation loop described in latter sections.

Rule 5: In each mode, if the publisher has no revenue for 5 periods, the game will cease to exist (die) and is not replaced by the simulation.

In the subscription model, during each period the game publisher earns revenue of

$$R_t = F_t n_t \qquad [4.4]$$

Similarly, in the single purchase model, the game publisher earns revenue each period of

$$R_t = P_t Q_t \qquad [4.5]$$

To allow revenue comparisons between models, in both models, revenue is discounted to the present value in the initial period:

$$PV_t = \frac{R_t}{\left(1 - \frac{r}{12}\right)^t} \qquad [4.6]$$

Where r is the publisher's internal rate of return. So that total revenue is

$$R = \sum_{t=0}^{T} PV_t \qquad [4.7]$$

By computing net present value (NPV) in this manner, we are able to compare the results of the different pricing strategies for both single purchase and subscription models. This is critical as without any discounting, the subscription model has a built-in advantage.

4.2.1.3 Links

Consumers who are not linked to the game publisher or any players of the game have no awareness of the game. Players who choose to subscribe to a game have a direct link created between the game publisher and themselves. This means that they maintain awareness of the game and treat the game publisher as a neighbor even if they stop playing the game due to a price change. Awareness does not disappear over time as links (both initial and manufactured) are not removed from the environment. The links between players are randomly generated. The actual number of links between a consumer and other consumers can be either deterministic or an independent, identically distributed (iid) random variable with a mean of L_P and a standard deviation of σ_L. In the case of a deterministic L_P, while there is a maximum of $N * L_P$ total links between players, it is possible that two links could be generated over the same path. This means that the number of links can be lower than the maximum as a duplicated link counts as a single link instead of two links. Also, links between players are undirected links, that is, a link going from L_i to L_{i+1} is no different from a link going from L_{i+1} to L_i. This is an important distinction as it allows awareness to “move” in either direction as the simulation environment changes.

4.2.2 Simulation Mechanics

As mentioned in earlier sections, this simulation was conducted using NetLogo. NetLogo is particularly well suited for this type of problem as it is both flexible, thus allowing us to vary a wide range of inputs, and robust.

4.2.2.1 Layout

Figure 4.1.2 shows the layout of the simulation environment. In this example there are 80 consumers with two links to other consumers and a single game publisher with initial links to five players (the beta-test group). In this environment, red triangles are consumers who are as yet potential customers. The circle is the game publisher and the colored triangles are players who were in the beta-test group or have been influenced by pre-release market enthusiasm for the respective game.

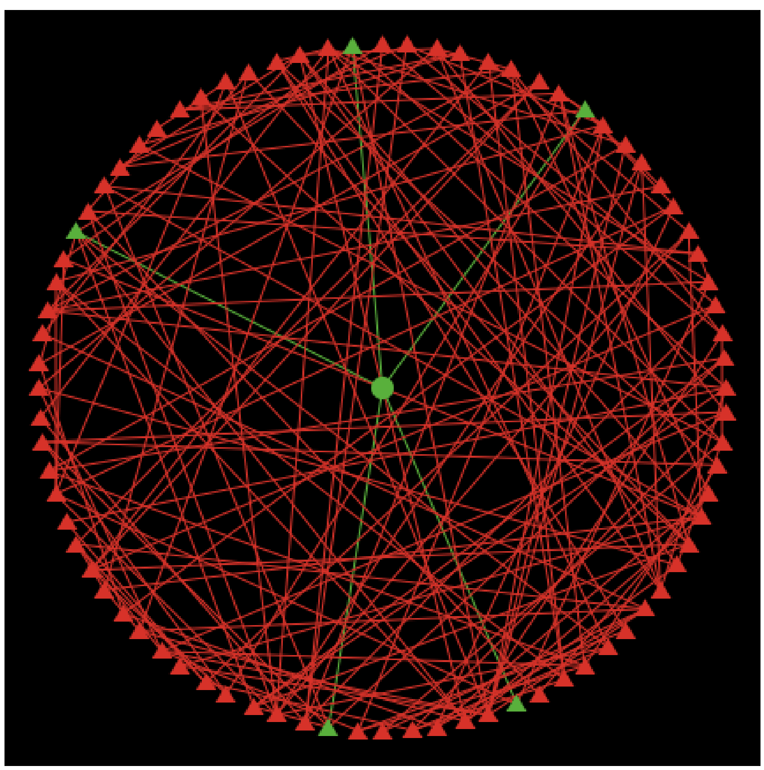

Figure 4.1.2: Simulation environment

4.2.2.2 Procedures

This section outlines the procedures and processes of the revenue dependent subscription pricing model. The oscillation and steady price models are simpler versions of the procedures outlined in this section. The simulation is initialized according to the user specified parameters. These parameters provide inputs for the initial period and provide the setup links. Each period that follows uses the procedure outlined in Table 4.1.2. Graphical representation of the simulation process for the subscription model is shown in Figure 4.1.3. This procedural loop will continue until the user terminates the session or stopping criteria is reached.

Table 4.1.2 – Simulation procedures

Step	Action
1	Consumers evaluate game in terms of neighbors and price
2	Consumers link to game if purchased
3	Game publisher evaluates revenue and sets price for next period
4	GUI updates
5	Simulation indexes 1 increment and returns to Step 1

For a consumer there are two decision steps in evaluating the game in terms of neighbors and price. The first step is two stage in the form of a conditional “AND” statement. So long as $p_{i,t} > 0$, the player knows the game exists. Since the simulation loop has a 2 stage “IF” decision process for the player, either of them could trigger a failure to purchase. The second IF is dependent on price and the consumer’s budget. The second decision step considers the magnitude of $p_{i,t}$. Put simply, assuming the player is aware of the game, or that at least one neighbor is either playing the game or is the game publisher, then the player will evaluate the game’s price in terms of their budget after the awareness check and then check to see if they are actually interested in playing the game as determined by $p_{i,t}$. In terms of logic, the players will carry out the following actions:

1st decision – 2 stage IF:

1) If $p_{i,t} > 0$ (i.e. $G_{i,t} > 0$)
2) If $B_i \geq P_t$?

- If either of these checks fail, the player will skip the second decision will not buy the game during period t.

2nd decision – Another IF:

3) Generate a random number $q_{i,t} \sim U(0,1]$
4) If $p_{i,t} > q_{i,t}$?

- If this fails, the player will not buy the game during period t.

At this point, the game publisher has to evaluate the changes in revenue between t and $t-1$ and make a decision concerning price. The simulation updates the GUI, indexes the time increment by one and the simulation loop begins anew.

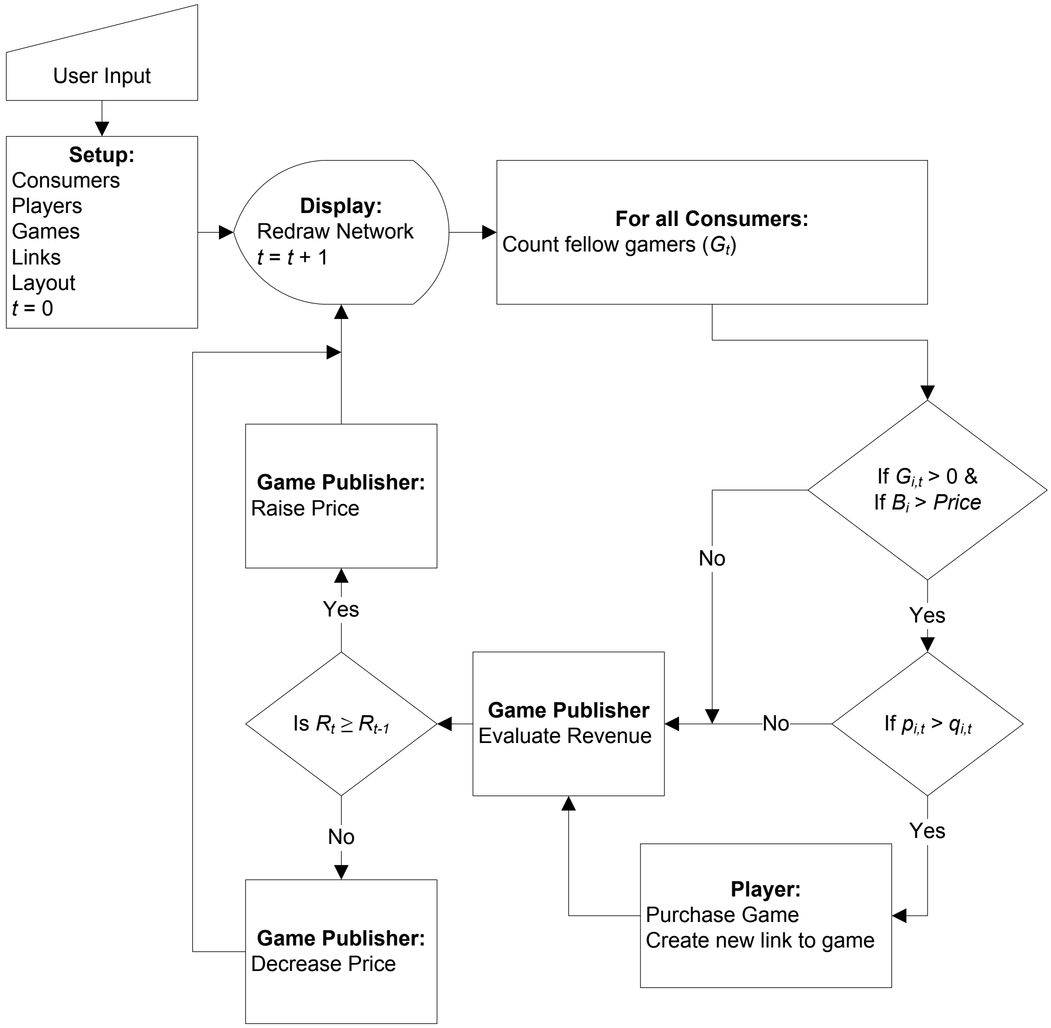

Figure 4.1.3: Simulation flowchart

4.2.2.3 Simulation Setup and Initialization

As described earlier, there are several pricing models that the simulation allows the user to select from. The range of user specified values does not change between models, however, certain pricing schemes use different additional or fewer parameters depending on the pricing scheme, see Table 4.1.3. Of the different parameters, it is important to note that in the initialization process, the user specifies the size of the initial group (i.e. the size of the beta-test group). This group is connected to a web of consumers which drives the growth of the game through these connections to additional consumers allowing us to model network externalities and their impacts on subscription sales.

Table 4.1.3 – Simulation parameter values for subscription pricing model

User Specified Parameter	**Symbol**	**Value Range**
N	N	Between 10 and 1000
Mean_Player_Links	L_P	Between 1 and 10
Player_Link_StDev	σ_L	Between 0 and 5
Network_Externalities	Y	Between 0.1 and 1.0
#_Game_Links	n_0	Between 1 and 30
Mean_Budget	μ_B	Between 1 and 100
Budget_StDev	σ_B	Between 0 and 20
Price	P_1, F_1	Between 1 and ∞
Price_Change	ΔP_t, ΔF_t	Between 0 and ∞
Retention_Rate	δ	Between 0.1 and 1.0
Discount	φ	Between 0.01 and 1.0
IRR_Publisher	r	Between 0.01 and 1.0
Duration	T	Between T and ∞
Periods_Discounted	H	Between 6 and ∞

4.3 Simulation Experiment

4.3.1 Subscription Pilot Experiment

This pilot experiment features a fixed price subscription based simulation. The purpose of this experiment is to find the optimal price for the game publisher to charge for the game in a fixed price subscription model. The parameter values used in the simulation for this experiment are shown in Table 4.2.1. As described in earlier sections, the links between consumers were randomly generated as were the consumers' budgets.

Repeated runs of the simulation were conducted with a search for the best price F_t using the bisection method, see Table 4.2.2 and Figure 4.2.1. $\bar{R}$ is the mean total revenue for each price tested earned by the publisher over the five runs whereas $\bar{n}$ is the mean number of subscriptions. In each run, the simulation operated for 36 cycles ($T = 36$)

with no user specified changes permitted other than varying price. As a fixed price strategy, price was not changed during any run. While the simulation was always run for five iterations with each price, an abbreviated example with two sample simulation runs with the optimal prices for this pricing strategy is shown in Table 4.2.3 along with the different variables monitored during the simulation. Given the parameters specified, the optimal subscription fee for this model exists between \$7 and \$8. Figures 4.2.2 – 4.2.4 show for the optimal price $F_1 = 7$, the sales per period, how total revenue changes per period, and the number of players linked to the game publisher per period respectively. The number of sales per period peaks around period 10 and then oscillates up and down due to the constantly changing values of $p_{i,t}$.

Table 4.2.1 – Pilot experiment

Simulation Name	**Notation**	**Value**
N	N	1000
Mean_Player_Links	L_P	5
Player_Link_StDev	σ_L	0
#_Game_Links	n_0	10
Mean_Budget	μ_B	10
Budget_StDev	σ_B	2
Price	F_1	10
Price_Change	ΔF_t	0
Network_Externalities	Y	0.5
Retention_Rate	δ	1.0
Discount	φ	0.4
IRR_Publisher	r	0.3

Table 4.2.2 – Bisection method

$\boldsymbol{P_t}$	**Mean Total Revenue ($\bar{R}$)**	**Mean Quantity Sold ($\bar{n}$)**
13	\$ 572.	65
5	\$ 101,665.	31,888
9	\$ 92,134.	16,204
7	\$ 127,571.	28,585
8	\$ 119,313.	23,665
6	\$ 117,482.	30,943

Figure 4.2.1: Bisection method – subscription

Table 4.2.3 – Variables monitored and results

Simulation Name	Description	Notation	Results Run 1	Results Run 2
Price/Fee	Optimal Fee	F_t^*	$ 7	
Total_Active_Players	Number of players playing the game during period t	n_t	See Figure 2.2	
Total_Revenue	Revenue earned over T	R	$ 127,721	$ 128,361
Revenue	Revenue earned during period t	R_t	See Figure 2.3	
Total_Sales	Total number of sales over T	n	28,552	28,621
Sales	Sales in period t	n_t	See Figure 2.2	
Losses	Number of players in period t priced out due to ΔF_t or via $(1-\delta)$		N/A	
Rejoins	Number of players in period t who rejoin game after leaving		N/A	
Links	Number of links generated in period t by buyers not in the beta group		See Figure 2.4	
Flat_Revenue	Number of periods where $R_t = 0$		0	0
Max_Sales	n_t of most profitable period over T		897	894
Max_Period	Most profitable period t		12	21
Min_Sales	n_t of least profitable period over T where $n_t > 0$		31	34
Min_Period	Least profitable period t		0	0
Change	Largest change in n_t over T		210	200
Change_Period	Largest changing period t		3	4

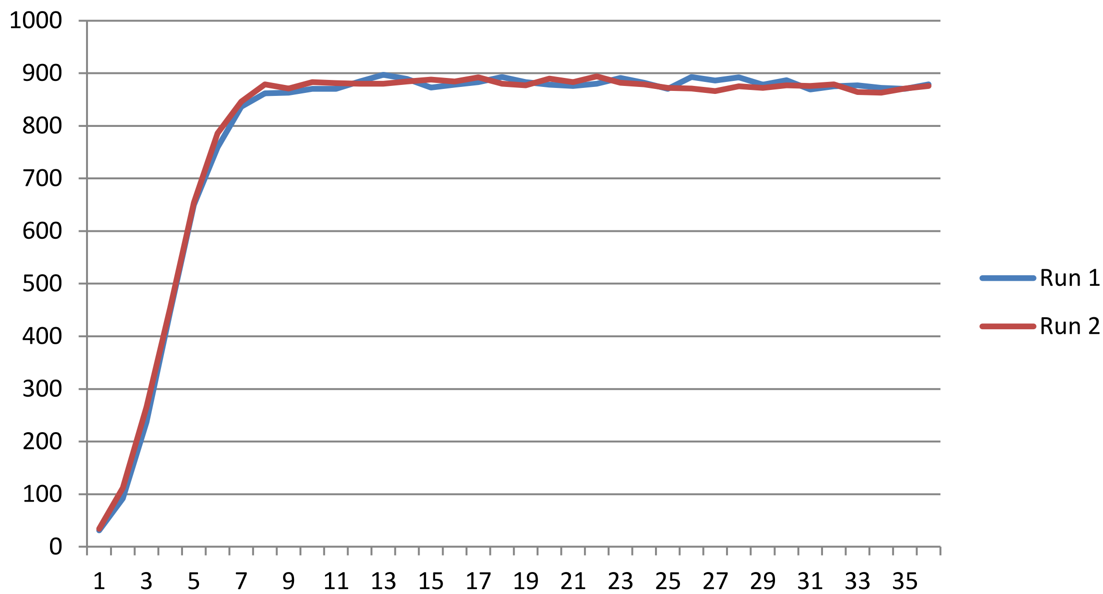

Figure 4.2.2: Subscriptions

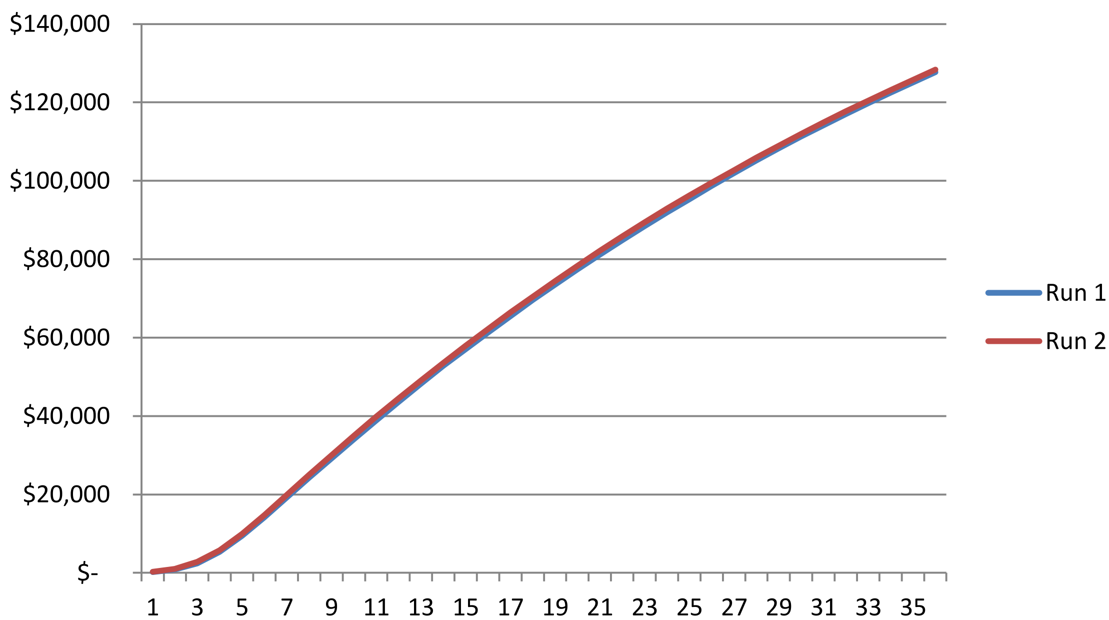

Figure 4.2.3: Total revenue

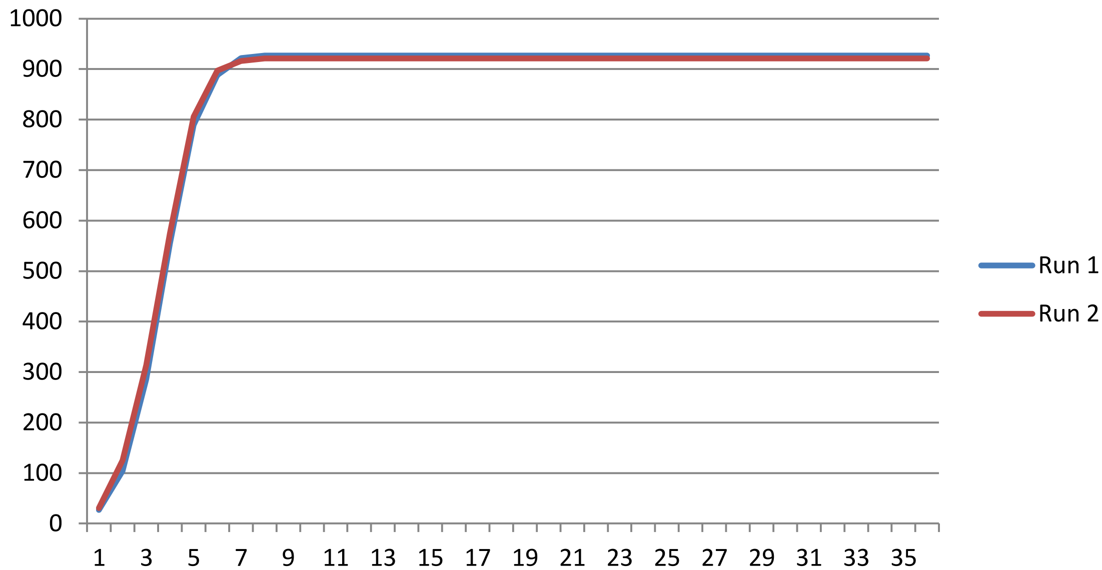

Figure 4.2.4: Number of player links to game publisher

4.3.2 Single Purchase Pilot Experiment

This pilot experiment features a fixed price single purchase based simulation. The parameter values were not changed from those shown in Table 4.2.1. Repeated runs of the simulation were conducted with a search for the best price P_t using the bisection method, see Table 4.2.4 and Figure 4.2.5.

A notable difference between the single purchase and the subscription models is the discounting of the players' budget. In the subscription model, consumers have a budget of

$$B_i = b_i \tag{4.8}$$

Whereas in the single purchase model the consumer looks at their current budget amount of b_i as well as the present value of the next several periods. By discounting the budget per period, we make the models comparable. Thus, the consumer uses a budget of

$$B_i = \sum_{t=0}^{36} \frac{b_i}{\left(1 - \frac{\varphi}{12}\right)^t} \qquad [4.9]$$

$\bar{R}$ is the mean total revenue for each price tested earned by the publisher over the five runs whereas $\bar{Q}$ is the mean number of game sales in each period. In each run, the simulation terminated early (before $t = 36$) per to the revenue rule of the publisher as all possible sales had already happened. Two example simulation runs with the optimal prices for this pricing strategy is shown in Table 4.2.5 along with the different status variables monitored during the simulation. Given the parameters specified, the optimal price for this model exists between \$162 and \$163. Figures 4.2.6 – 4.2.8 show for the optimal price $P_0 = 163$, the sales per period, how total revenue changes per period, and the number of players linked to the game publisher per period respectively.

Table 4.2.4 – Bisection method

P_t	Mean Total Revenue ($\bar{R}$)	Mean Quantity Sold ($\bar{Q}$)
250	\$ 37,198	179
100	\$ 46,122	990
175	\$ 130,496	805
138	\$ 122,798	955
156	\$ 130,233	898
166	\$ 133,031	865
161	\$ 133,010	888
163	\$ 133,552	881
162	\$ 133,539	888

Figure 4.2.5: Bisection method

Table 4.2.5 – Variables monitored and results

Simulation Name	**Description**	**Notation**	**Results Run 1**	**Results Run 2**
Price	Optimal Price	P_t^*	$ 163	
Total_Active_Players	Number of players playing the game during period t	n_t	See Figure 2.8	
Total_Revenue	Revenue earned over T	R	$ 134,336	$ 133,052
Revenue	Revenue earned during period t	R_t	See Figure 2.7	
Total_Sales	Total number of sales over T	Q	883	887
Sales	Sales in period t	Q_t	See Figure 2.6	
Losses	Number of players in period t priced out due to ΔP_t or via $(1-\delta)$		0	0
Rejoins	Number of players in period t who rejoin game after leaving		0	0
Links	Number of links generated in period t by buyers not in the beta group		See Figure 2.8	
Flat_Revenue	Number of periods where $R_t = 0$		0	0
Max_Sales	Q_t of most profitable period over T		287	287
Max_Period	Most profitable period t		3	3
Min_Sales	Q_t of least profitable period over T where $Q_t > 0$		2	8
Min_Period	Least profitable period t		7	6
Change	Largest change in Q_t over T		115	123
Change_Period	Largest changing period t		2	2

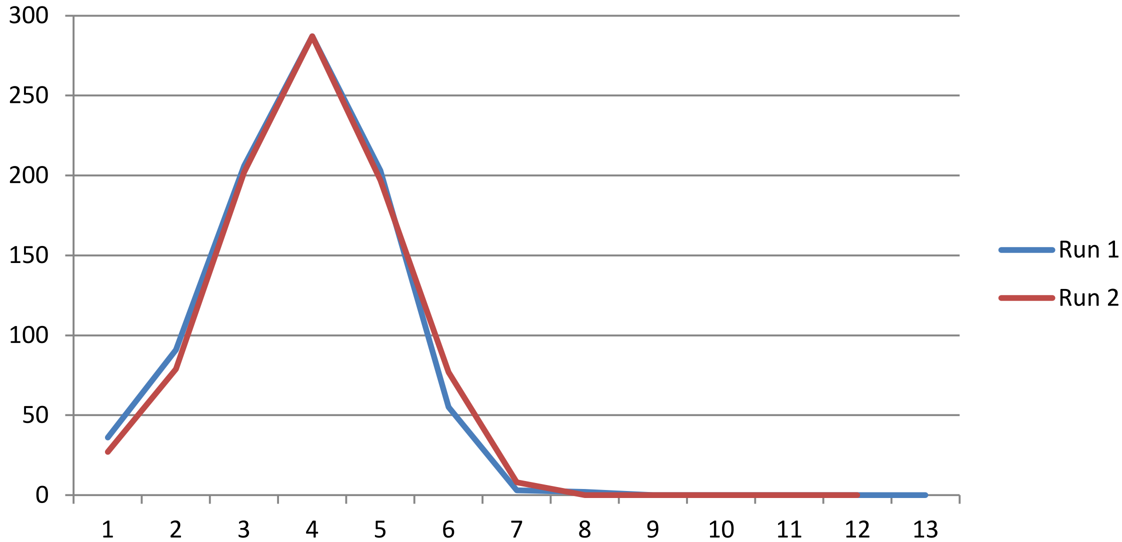

Figure 4.2.6: Sales

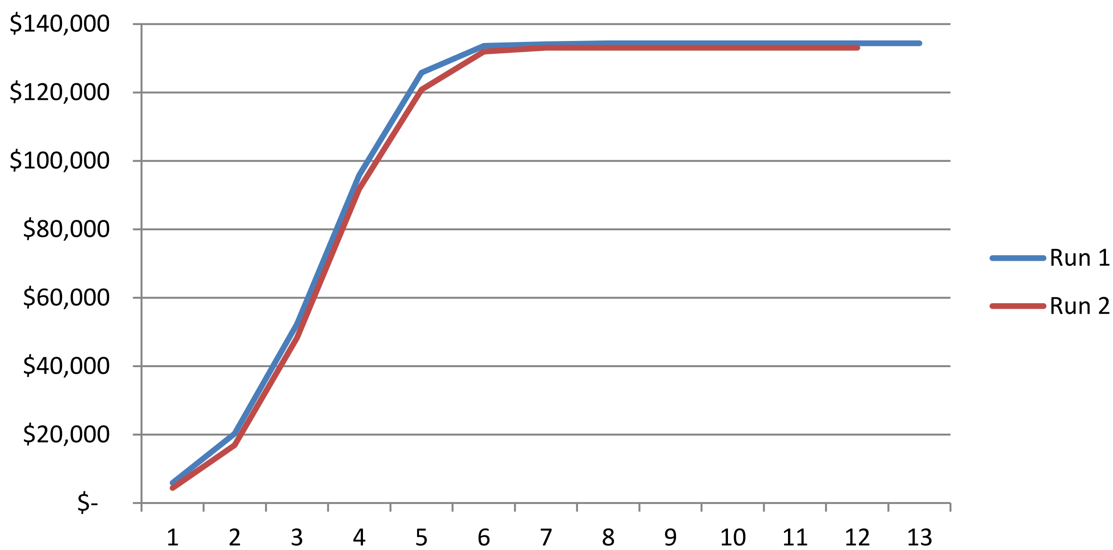

Figure 4.2.7: Total revenue

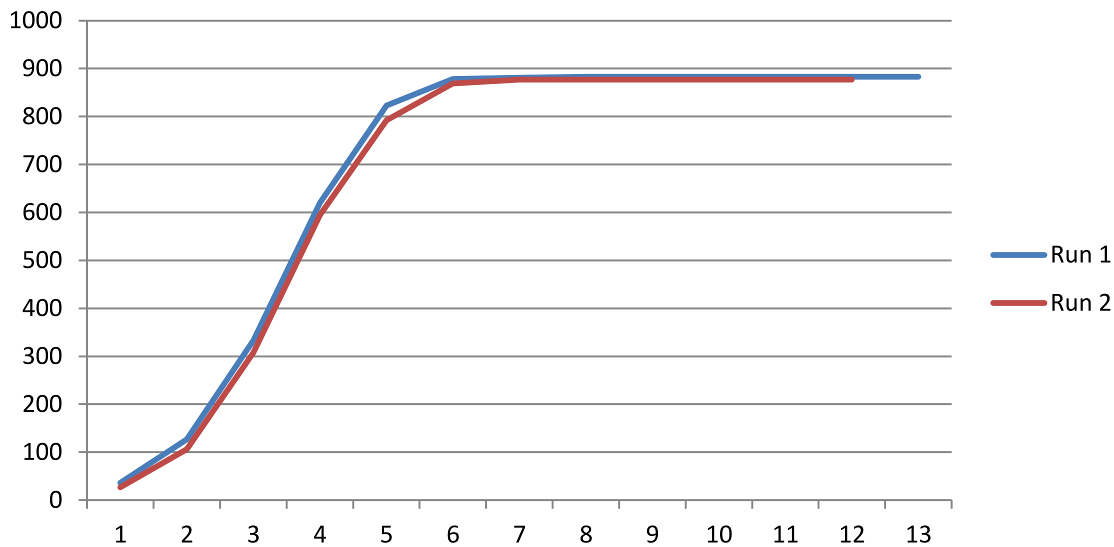

Figure 4.2.8: Number of player links to game publisher

4.3.3 Implementation

A NetLogo program was created to run multiple passes through each combination of variables. By using several "while" loops, the program identifies the optimal price for each combination (pricing strategy, Y, Lp, retention rate, discount horizon, and n_0) using the search method described in Section 4.3.3.2 and 4.3.3.3. Upon completion of this step, the program runs a simulation trial with the currently selected group of aforementioned parameters, see Section 4.3.3.4. Figure 4.2.9 shows the loops in which the simulation program moves through. The shaded processes each call the procedure shown in Figure 4.1.3.

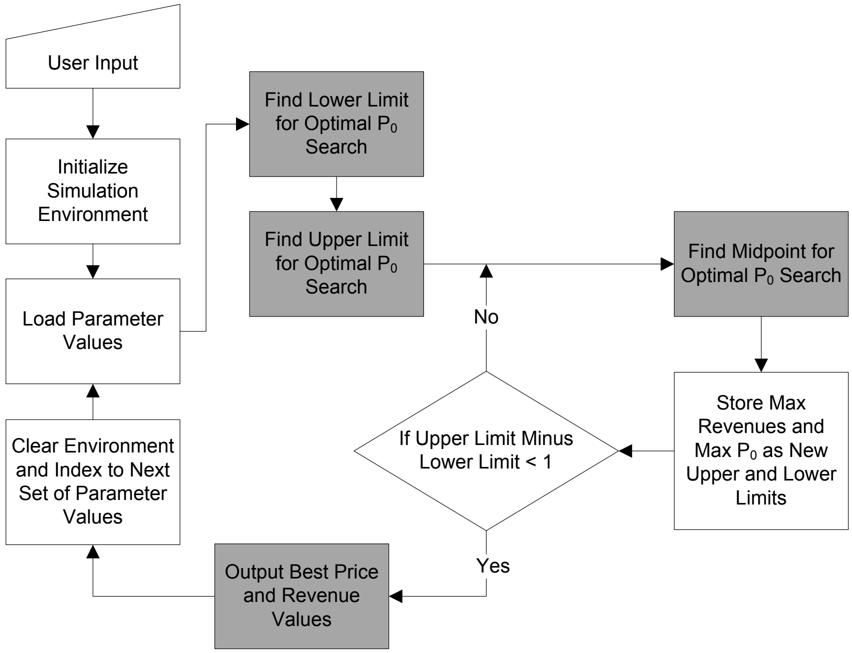

Figure 4.2.9: Simulation experiment

4.3.3.1 Initialization and Program Startup

The values for the simulation's parameters are shown in Table 4.3.1. All 1,296 solutions were identified.

Table 4.3.1 – Parameter values

Simulation Name	Symbol	Value	Notes
N	N	1000	
Mean_Player_Links	L_P	4, 7, 10	1
Player_Link_StDev	σ_L	0	
#_Game_Links	n_0	10, 30	1
Mean_Budget	μ_B	\$ 4.00	
Budget_StDev	σ_B	\$ 0.80	
Price_Change	$\Delta P_t, \Delta F_t$	$0.15 * \bar{B}_i$	2
Network_Externalities	Y	0.2, 0.5, 0.8	1
Retention_Rate	δ	0.4, 0.6, 0.8	1
Discount	φ	0.20	3
IRR_Publisher	r	0.12	3
Duration	T	36	4
Periods_Discounted	H	12, 24, 36	1

Notes
1) Systematically varied by experiment
2) B_i is used for single purchase strategies. For subscription the mean of b_i is used
3) Nominal APR discounted monthly
4) Simulation may end early due to revenue rule of game publisher

Since increasing the discount horizon has the same effect as decreasing the consumers' discount rate for single purchase strategies we only vary the discount horizon (H), which means that the consumers' discounted budget is:

$$B_i = \sum_{t=0}^{H-1} \frac{b_i}{\left(1 - \frac{\varphi}{12}\right)^t} \qquad [4.10]$$

Since the program starts at $t = 0$, the discounting of a consumer's budget goes from 0 to $H - 1$.

The program was initialized with the lower values for each of the parameters used (i.e. if $Y = [0.2, 0.5, 0.8]$ then the program will begin at $Y = 0.2$). This means that there are 1,296 total combinations or 162 for each of the different pricing strategies all of which are indexed through via multiple nested "while" loops. We hold the distribution of consumers' budgets as a constant as well as N, duration, customer discount rate, and IRR of the publisher. When applicable, the amount of the price change between periods was set at $0.15 * \bar{B}_i$. In generating the consumer agents' budgets, the distribution is truncated such that all values for b_i are greater than or equal to zero. This safety measure exists because there is a possibility for some distributions generating negative consumer budgets. For the distribution used in this experiment, this failsafe was not tripped and the program did not need to adjust any budgets.

4.3.3.2 Optimal Price Search

For each set of parameters the program will try to find the optimal price via the bisection method described in Section 3.2. The program selects high and low points for the bisection method two times the calculated mean of players' budgets and at 0.001 of the calculated mean of players' budgets respectively.

In single purchase strategies, the calculated mean of players' discounted budgets is used. For program execution speed, this calculated mean is determined only once per simulation method run and is then stored in a self-clearing manner. The simulation method is then run for five iterations for each of these and the mean total revenue is recorded for each. The midpoint price between these two price points is selected and the simulation method is run again for five iterations with the mean total revenue for these five iterations being recorded. The two price points that give the greatest mean total revenue are selected as endpoints and a new midpoint is calculated. This process repeats until the two endpoints are less than \$1.00 apart. The simulation stores this optimal price as the optimal value for P_0 for the current set of parameters.

Due to the random number generator and also due to the failsafe described in Section 3.3.1, there exists the possibility that the calculated mean of players' budgets is not perfectly equal to the proscribed mean, necessitating another failsafe. In the event that the initial search space was inadequate (i.e. P_0 is determined to be too close to the upper initial endpoint), the program can correct this. If the difference between the upper initial endpoint and the optimal P_0 is less than 1, the program will double the search area. By using the calculated mean of players' budgets $(\bar{b}_i$ or $\bar{B}_i)$ instead of the mean of the underlying distribution (μ_B), the search process is quicker by one or two steps in the bisection method when the actual mean is slightly less than the proscribed mean. If the proscribed mean is slightly less than the actual mean, this means that the search area is wider and there is less risk of the optimal P_0 falling near an initial endpoint. For the distribution used in this experiment, these phenomena did not occur and the program did not need to widen its search area.

4.3.3.3 Simulation Procedure

The simulation procedure is a version of the pilot experiment designed for speed. It is initialized according to the user specified parameters for player budget, discount rates, etc. This method runs for five iterations for each price examined during the bisection method described in Section 4.3.3.2 and is reinitialized each time. In other words, before any iteration of the five starts, all agents are cleared and the setup method is run anew to repopulate the network. After five iterations the simulation procedure returns the mean of total revenue for these five iterations as well as the maximum and minimum total revenues earned in addition to the mean total sales (or subscriptions).

4.3.3.4 Simulation Trial

Using the optimal price found according to Section 4.3.3.2 and with the values selected according to it the program's progress through the loops described in Section 4.3.3.1, the simulation procedure was run five times with the optimal value for P_0 and (where appropriate) and a price change as outlined earlier. This acts as a loading method for data reporting that enables the program to run faster and fit within the memory constraints of NetLogo. At the conclusion of the trial, a data file is opened and outputs for the different parameters' values, the revenue information calculated as above, as well as pricing information (P_0 and the price change) are written. At this point, the program closes the file, exits the write method, and moves back up to the next combination in the while loop. This process continues for all 1,296 combinations.

4.4 Simulation Results

4.4.1 Subscription Model Results

There are four pricing strategies available for use in the subscription model. These are Fixed Price (FP), Revenue Seeking (RS), Oscillation Low, High, Low… (O1), and Oscillation High, Low, High… (O2). Different strategies may work better for the different parameter combinations as outlined in earlier sections (see Figures 4.3.1 – 4.3.3). Table 4.3.2 shows the percentage of problems for which each strategy was best. The simulation program confirms the findings of Chapter 2. An O1 strategy was best 78 % of the time. For two of the parameters studied (n_0 and L_p) we observe that these parameters have little impact within the strategy, that is, the revenue earned by each strategy is consistent regardless of the level of n_0 and L_p. This is not the case across strategies as each different strategy performs at a different level which remains consistent according to the point raised above. A significant difference exists for Y in that the effects of network externalities do measurably impact the revenues earned via each strategy, particularly at $Y = 0.8$. This means that strength of network externality conditions determine the specific strategy that is optimal for the game publisher. In considering the performance of the different strategies, we note the following:

1) In most circumstances, a game publisher who is following a subscription based pricing model will find an O1 strategy to be one that provides superior results.
2) The poor performance of RS strategy is due to the effects of how the game publisher increases price to a point beyond the customers' budgets and then oscillates back and forth just above and below said budget. This is different

from the O1 or O2 oscillation as the RS strategy increases to a suboptimal price and then oscillates around that price.

3) The RS strategy was the most inconsistent of the four subscription based pricing strategies. This high degree of variability in outcomes results in this strategy behaving in unexpected ways such as shown in Figure 3.2 where revenue would be expected to be increasing in L_p. We make the same observation about the O2 strategy and note that we expected revenue to increase alongside increases in L_p.
4) The marked differences between the revenues earned by a publisher following an O1 vs. an O2 strategy stem from the importance of network externalities and the fact that an O2 strategy immediately attempts to raise price instead of increasing market size.
5) In examining the variability of the revenues earned by the different strategies (see Table 3.3 for an example) we find that a publisher following either a FP or O1 strategy will earn the most consistent stream of revenues.
6) A FP strategy provides revenues close to that of the O1 strategy in many cases. This strategy allows a publisher to earn considerable revenue without the price changes so unpopular with consumers.
7) Beta test group size is important as all strategies earn more revenue with a larger test group size.

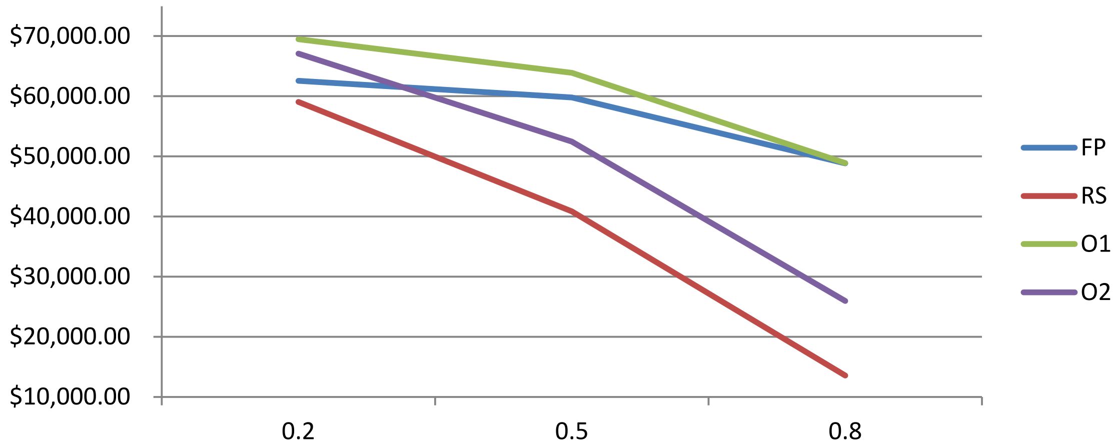

Figure 4.3.1: Revenue for network externalities of subscription pricing strategies

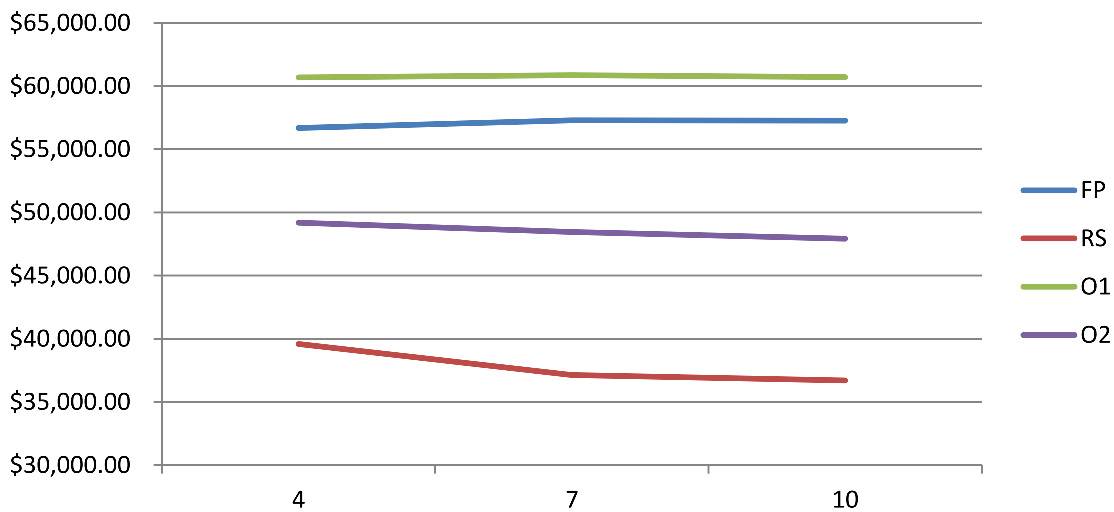

Figure 4.3.2: Revenue for number of player links of subscription pricing strategies

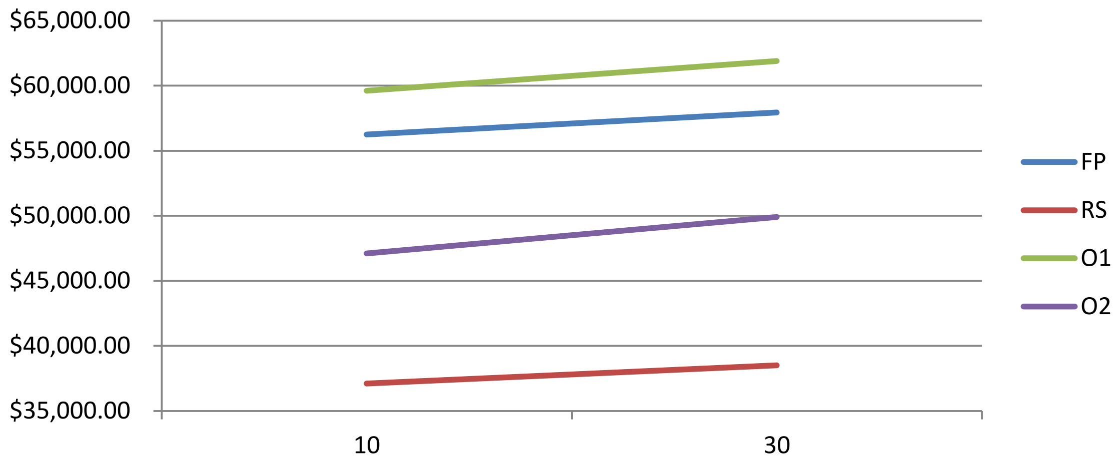

Figure 4.3.3: Revenue for beta test group size of subscription pricing strategies

Table 4.3.2 – Optimal subscription strategy distribution

Subscription Strategy	Overall	Y			L_p			n_0	
		0.2	0.5	0.8	4	7	10	10	30
FP	22%	0%	0%	67%	17%	17%	33%	22%	22%
RS	0%	0%	0%	0%	0%	0%	0%	0%	0%
O1	78%	100%	100%	33%	83%	83%	67%	78%	78%
O2	0%	0%	0%	0%	0%	0%	0%	0%	0%

Table 4.3.3 – Variability in optimal solutions for different values of y in five runs

$Y = 0.2$	Mean Revenue	Max – Min	Min	Max
FP	$ 62,590.84	$ 2,250.43	$ 61,502.02	$ 63,752.46
RS	$ 59,050.59	$ 9,491.43	$ 53,985.87	$ 63,477.30
O1	$ 69,502.39	$ 1,237.89	$ 68,892.97	$ 70,130.86
O2	$ 67,119.70	$ 3,343.65	$ 65,396.18	$ 68,739.84
$Y = 0.5$				
FP	$ 59,802.33	$ 1,253.15	$ 59,164.18	$ 60,417.33
RS	$ 40,832.42	$ 10,424.98	$ 35,324.03	$ 45,749.01
O1	$ 63,883.26	$ 1,750.43	$ 62,997.35	$ 64,747.79
O2	$ 52,483.02	$ 4,178.94	$ 50,424.08	$ 54,603.01
$Y = 0.8$				
FP	$ 48,854.10	$ 2,847.64	$ 47,397.78	$ 50,245.42
RS	$ 13,518.64	$ 8,067.18	$ 9,497.03	$ 17,564.21
O1	$ 48,870.98	$ 3,377.25	$ 47,207.46	$ 50,584.71
O2	$ 25,931.96	$ 4,675.39	$ 23,588.25	$ 28,263.64

4.4.2 Single Purchase Model Results

The single purchase model has the same four pricing strategies available. As with the subscription model, different strategies may be more suitable for different parameter combinations (see Figures 4.3.4 – 4.3.8). Table 4.3.4 again shows the percentage of times for which each strategy was best. Unlike in the subscription model, in the single purchase model all parameters affect revenue. In examining revenue changes for the different strategies as a result of changing parameters, we note the following:

1) In most circumstances, a game publisher who is following a single purchase pricing model will find an RS to be one that provides superior results.
2) The performance of the RS strategy is due to the effects of how the game publisher increases price to a point beyond the customers' budgets a single time before attempting to skim the rest of the market (i.e. RS is a skimming strategy)
3) When retention rate is low, a publisher should not follow the RS strategy. However, the RS strategy provides significantly higher revenues than the other strategies at high retention rate levels, the same of which occurs when considering strength of network externalities. Unlike the other strategies which stay in the same price area throughout the game, the RS strategy can go much higher in price. This means that when retention rate is low and network effects are negligible, a consumer may have several chances to buy the game at a price they can afford in these three strategies, but only one or two chances to buy the game at a price they can afford when a publisher is following the RS strategy.

4) The RS and O2 strategies were the most inconsistent (highest variability) of the four single purchase strategies, whereas a publisher following either a FP or O1 strategy will earn the most consistent stream of revenues.

5) An O1 strategy has a revenue curve that is decreasing in n_0 (see Figure 4.3.8). This drop is due to the nature of the beta test group and how the members already have a copy of the game in their possession. While an increased beta group size does allow the game to spread through the network faster thereby increasing total revenue by not losing it to discounting effects, it is also true with a slower initial spread of the game, the publisher has a better chance to capitalize on network externalities by charging a higher price. A large beta group causes purchases to occur too early.

6) The consumer discount horizon (H) has a strong effect on the revenue earned via each strategy.

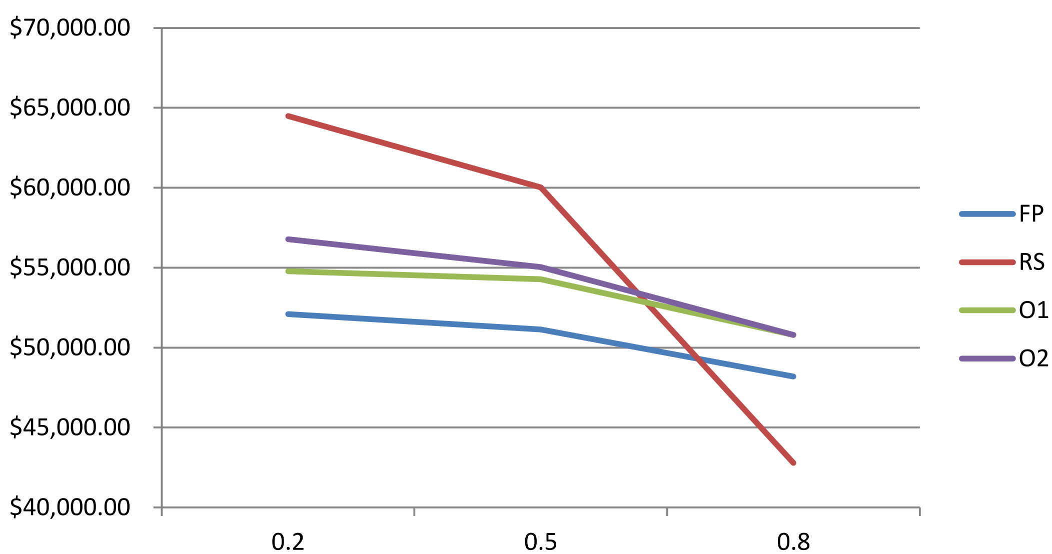

Figure 4.3.4: Revenue for network externalities of single purchase pricing strategies

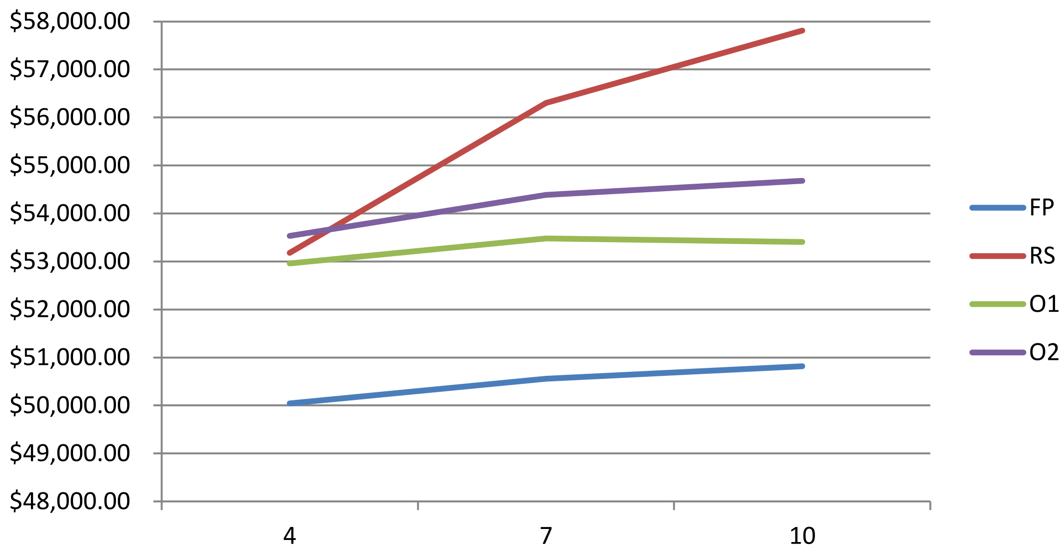

Figure 4.3.5: Revenue for number of player links of single purchase pricing strategies

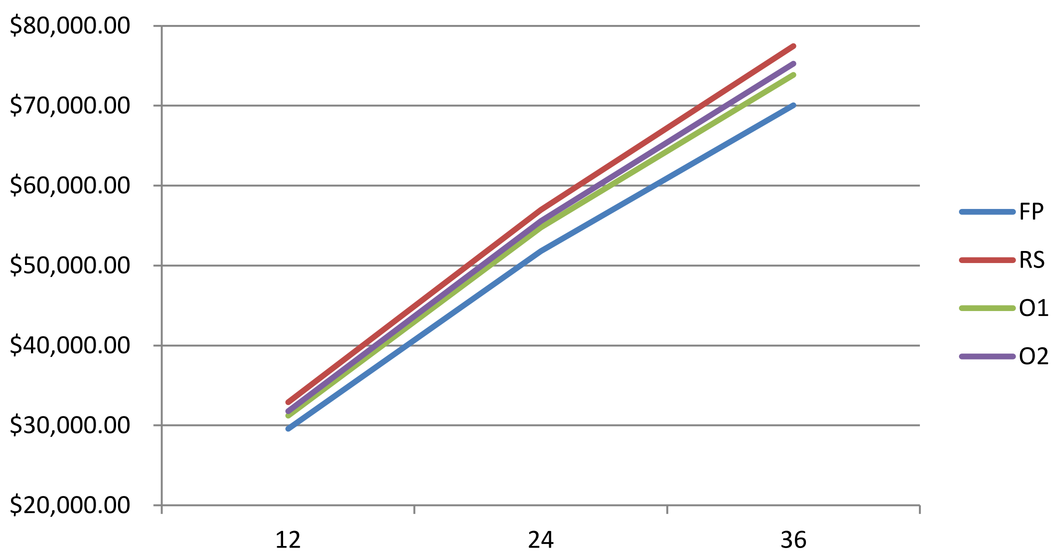

Figure 4.3.6: Revenue for periods discounted of single purchase pricing strategies

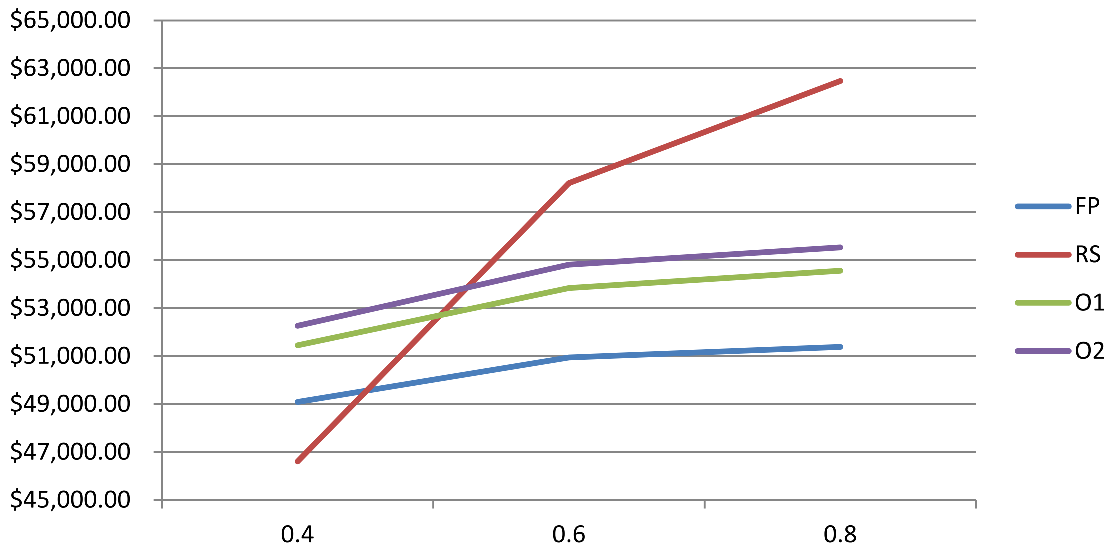

Figure 4.3.7: Revenue for retention rate of single purchase pricing strategies

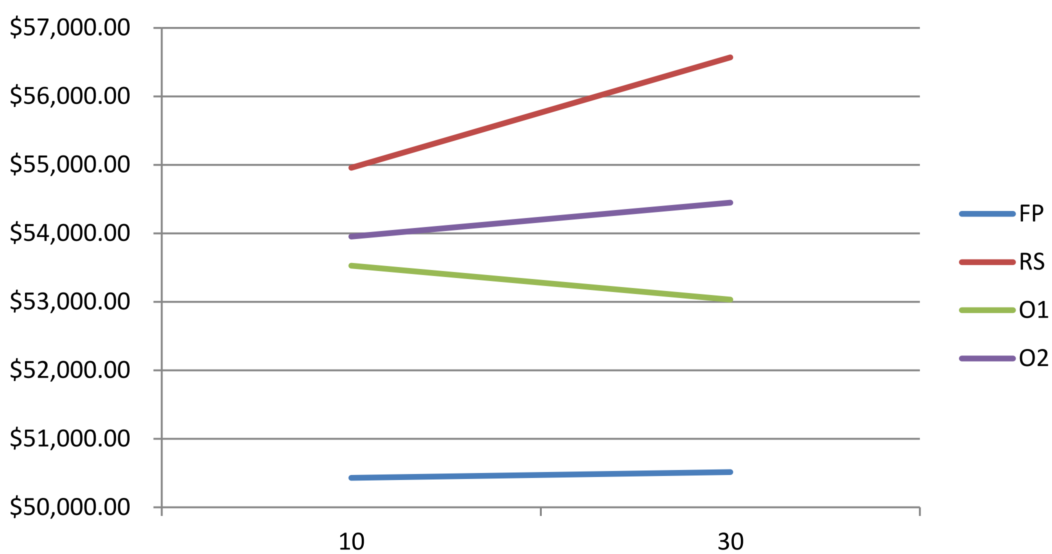

Figure 4.3.8: Revenue for beta test group size of single purchase pricing strategies

Table 4.3.4 – Optimal subscription strategy distribution

Single Purchase Strategy	Overall	Y 0.2	0.5	0.8	L_p 4	7	10	n_0 10	30
FP	0%	0%	0%	0%	0%	0%	0%	0%	0%
RS	81%	100%	94%	50%	74%	81%	89%	81%	81%
O1	10%	0%	0%	30%	15%	9%	6%	10%	10%
O2	9%	0%	6%	20%	11%	9%	6%	9%	9%
		δ 0.4	**0.6**	**0.8**	**H 12**	**24**	**36**		
FP		0%	0%	0%	0%	0%	0%		
RS		100%	94%	50%	81%	81%	81%		
O1		0%	0%	30%	7%	15%	7%		
O2		0%	6%	20%	11%	4%	11%		

4.4.3 Comparisons Between Single Purchase & Subscription Models

The subscription and single purchase models provide comparable results; however, there are certain circumstances when one is preferable to the other (see Table 4.3.5). The optimal prices for each strategy as found by the bisection method in the experiment are shown in Table 4.3.6 as well as the percentage of the market captured by each strategy.

1) Within each model, not all strategies are viable. In particular, the single purchase FP strategy and the subscription RS and O2 strategies are never optimal.
2) A game publisher who is uncertain about the consumer population preferences and the characteristics of the game would be advised to choose a single purchase RS strategy or a subscription O1 strategy as these are the best strategies 36 % and 48 % of the time respectively.
3) Revenue earned for each strategy in the single purchase model is dependent on the value of the different parameters to a greater degree than was the case for the strategies of the subscription model.

4) No strategy completely clears the market. That said, the single purchase RS strategy clears 91 % of the market and four other strategies clear 80 % of the market or more.
5) The performance differences of the RS strategy is due to the effects of how the game publisher increases price to a point beyond the customers' budgets once in the single purchase strategy before attempting to skim the rest of the market instead of oscillating above and below this upper budget limit as was the case in the subscription model.
6) In both the single purchase and the subscription model, the RS and O2 strategies were the most inconsistent (highest variability) of the four strategies.
7) Each parameter studied affects the optimal initial price charged by the publisher, regardless of the strategy used.
8) While both the subscription and the single purchase models have less revenue potential when y is high, the single purchase model provides superior results as network externalities only influence one purchase decision for each player instead of repeated purchase decisions for each player as is the case for the subscription model.

Table 4.3.5 – Optimal strategy distribution

		Y			L_p			n_0	
Strategy	**Overall**	**0.2**	**0.5**	**0.8**	**4**	**7**	**10**	**10**	**30**
FP (Sub)	6%	0%	0%	19%	2%	7%	9%	4%	0%
FP (SP)	0%	0%	0%	0%	0%	0%	0%	0%	0%
RS (Sub)	0%	0%	0%	0%	0%	0%	0%	0%	0%
RS (SP)	36%	33%	41%	35%	30%	39%	41%	28%	81%
O1 (Sub)	48%	67%	56%	22%	56%	44%	44%	59%	0%
O1 (SP)	5%	0%	0%	15%	7%	6%	2%	7%	7%
O2 (Sub)	0%	0%	0%	0%	0%	0%	0%	0%	0%
O2 (SP)	4%	0%	4%	9%	6%	4%	4%	2%	11%
		δ			H				
		0.4	**0.6**	**0.8**	**12**	**24**	**36**		
FP (Sub)		7%	9%	15%	15%	4%	0%		
FP (SP)		0%	0%	0%	0%	0%	0%		
RS (Sub)		0%	0%	0%	0%	0%	0%		
RS (SP)		39%	41%	0%	0%	28%	81%		
O1 (Sub)		44%	44%	85%	85%	59%	0%		
O1 (SP)		6%	2%	0%	0%	7%	7%		
O2 (Sub)		0%	0%	0%	0%	0%	0%		
O2 (SP)		4%	4%	0%	0%	2%	11%		

Table 4.3.6 – Optimal prices and fees

Strategy	Mean P_0 or F_0	% of Market	y 0.2	0.5	0.8	L_p 4	7	10
FP (Sub)	$ 2.50	79 %	$ 2.97	$ 2.28	$ 2.25	$ 2.47	$ 2.48	$ 2.56
FP (SP)	$ 61.38	86 %	$ 62.20	$ 61.54	$ 60.39	$ 61.13	$ 61.67	$ 61.34
RS (Sub)	$ 1.46	39 %	$ 1.64	$ 1.95	$ 0.78	$ 1.36	$ 1.42	$ 1.59
RS (SP)	$ 64.81	91 %	$ 79.84	$ 63.09	$ 51.50	$ 59.97	$ 65.68	$ 68.78
O1 (Sub)	$ 2.25	80 %	$ 2.26	$ 2.25	$ 2.25	$ 2.25	$ 2.25	$ 2.25
O1 (SP)	$ 58.83	89 %	$ 59.42	$ 59.32	$ 57.76	$ 58.78	$ 58.86	$ 58.86
O2 (Sub)	$ 3.75	47 %	$ 3.75	$ 3.75	$ 3.76	$ 3.75	$ 3.75	$ 3.75
O2 (SP)	$ 71.68	88 %	$ 72.69	$ 72.48	$ 69.88	$ 71.68	$ 71.83	$ 71.54
	n_0 10	30	δ 0.4	0.6	0.8	H 12	24	36
FP (Sub)	$ 2.38	$ 2.63	$ 2.50	$ 2.45	$ 2.56	$ 2.50	$ 2.48	$ 2.53
FP (SP)	$ 60.63	$ 62.13	$ 60.83	$ 61.69	$ 61.62	$ 36.03	$ 62.90	$ 85.21
RS (Sub)	$ 1.33	$ 1.59	$ 1.48	$ 1.45	$ 1.45	$ 1.45	$ 1.45	$ 1.48
RS (SP)	$ 58.22	$ 71.40	$ 65.02	$ 61.65	$ 67.75	$ 38.06	$ 66.58	$ 89.79
O1 (Sub)	$ 2.25	$ 2.25	$ 2.26	$ 2.25	$ 2.25	$ 2.25	$ 2.25	$ 2.25
O1 (SP)	$ 58.69	$ 58.97	$ 58.02	$ 59.14	$ 59.34	$ 34.52	$ 60.35	$ 81.63
O2 (Sub)	$ 3.76	$ 3.75	$ 3.75	$ 3.75	$ 3.75	$ 3.76	$ 3.75	$ 3.75
O2 (SP)	$ 71.75	$ 71.62	$ 70.37	$ 71.98	$ 72.70	$ 42.03	$ 73.54	$ 99.48

CHAPTER 5: CONCLUSION

The preceding chapters provided the reader with an overview of online multiplayer games, presented two mathematical models for pricing online games, tested those models' sensitivity via a numerical experiment, and finally conducted a simulation experiment to find the best price for online multiplayer games. The following sections of this final chapter examine the different limitations in the approaches taken during this research, provide a roadmap for future research efforts, and end with a few concluding remarks.

5.1 Limitations

In Chapter 2 there is a limitation in the structure of the model. In the model we hold that utility in the current time period is a function of the number of players in the previous time period. To be more realistic, the utility in the current time period is actually a function of the number of players in the current time period as these are who a player is engaged with at that particular time. Also, the utility in the first time period is a function of both the beta test group, the number of players in the current time period, among several other factors. In the models presented, we used the beta test group and n_{t-1} in the utility function because if utility is a function of n_t, then we are faced with an intractable problem (i.e. utility is a function of the number of players in the game and the number of players in the game is a function of utility). We assume that the position that the beta test group size is a reasonable proxy for the number of players in the first period.

Also, in subsequent periods the number of players in the preceding period is an acceptable proxy for the number of players in the current period. While we do not consider this limitation to be one which impacts the usefulness of the model, for the sake of completeness it must be noted.

Also in Chapter 2, we should note that in the model we hold customer growth expectation of the game's growth factor (μ) static. μ is the consumers' expectation and the publisher may know that initial expectations held by the consumers are erroneous. For the purpose of this dissertation, μ is fixed; however, in reality μ is most likely dynamic as customer expectations are expected to change with regards to the game. There are possibilities of investigating when customers update their expectations based on past sales. Further, publishers may have information where they know expectations held by the consumers are overly optimistic or pessimistic; however, we do not investigate those situations in this dissertation.

There is one point about Chapter 3 that need to be made. For each parameter tested, we used low, medium, and high values. Even with only these three values for each parameter, we were faced with more than 6,000 parameter combinations, each of which required some time to calculate the best prices. While additional values for each parameter would be preferred, more than three values for each were not used due to the amount of processing time required.

There are a few limitations in Chapter 4 that merit discussion. The numbers provided in the results section are dependent upon the budget distribution. These results are applicable on for this budget. While a reader may look at the budget numbers and consider them to be inappropriate, we caution that these are for a set of consumers who are considering a single game. In point of fact, most game playing consumers actually play several games during any given period, switching between their gaming library according to their own tastes and preferences. This means that if a consumer has a budget of $20 per period then only a certain percentage of this budget is spent on the game in question and we have a capital allocation problem. Additionally, with only a single game in the simulation environment, the game publisher is a monopolist instead of in an environment where there is competition with many providers each having monopolistic tendencies.

Additionally concerning Chapter 4, the simulation experiment called the simulation procedure approximately 75,000 times in total taking a considerable amount of time to run. This forced us to limit the size of the population to 1,000 which ultimately resulted in the network being denser than we would typically see in industry. As presented, players were (depending upon the value of L_p) connected to up to ten other players or 0.1 % of the gaming population. While this does not seem unreasonable at first, when scaled up to a game with a population of several million, it does become an improbable number of connections between players. This means that awareness of the game spreads throughout the simulation much faster than may be the case in industry. Reducing L_p to lower levels was not possible as it resulted in wild swings in revenue due to the increased amount of variability in the simulation model during pilot testing. Attempts to increase the total number of players beyond 1,000 were not possible due to the volume of calculations each period and hardware limitations. Ideally, there would be a total number of consumers of several million, all linked to a random number of other players. With this exception of L_p, all of the other parameters have reasonable values given the size of the consumer base.

5.2 Future Work

In future efforts we intend to expand upon the framework laid out in the preceding chapters. In the mathematical model and numerical experiment we intend to make allowances for additional parameters in the utility function such as game genre and type of play as well as C_S and C_P. These are critical additions as different types of game become more or less popular with time. Following the release of the Lord of the Rings Trilogy, game publishers saw an increase in the popularity of high fantasy type games such as World of Warcraft. As of this writing, AMC's The Walking Dead was one of the more popular TV series and zombie themed movies were rising in popularity. Not coincidentally, the writers note a considerable surge of zombie or apocalypse themed games in popularity as well as the possible start of a decline in the high fantasy genre.

In the simulation experiment, we can introduce multiple games into the environment and examine the capital allocation problem that consumers face when they have a wider array of purchasing options. By varying the timing at which games are introduced into the market, we will be able to also look at the first mover advantage problem that game publishers face and to see what strategies game publishers can use to move into a market that is already saturated with offerings from rivals. This is an important area of future work as there are tens of thousands of games on the market as of this writing with more being introduced or announced every day.

Platform considerations are also an area that merits consideration. As of this writing both the Play Station 4 by Sony and the newest version of Microsoft's Xbox were slated for release within a year's time. Hardware improvements in these platforms and PCs as well as improvements in bandwidth and software capabilities mean that customers are able to enjoy a more immersive gaming experience than was possible in years past. With any cutting edge technology, there is a certain amount of hype and excitement that permeates the market. Considering where different platforms are in their development cycle is important when attempting to build a consumer utility function.

Additionally, we intend to consider the controversial issue of digital rights management (DRM). Game publishers have long had issues with software piracy and finding and testing pricing solutions that mitigate the effects of piracy or reduce the inclination to engage in piracy are of importance if game publishers are to continue to operate.

Finally, of the different revenue schemes introduced in Chapter 1, at this point we have only managed to examine two of them in detail. Future work must be done in examining these different pricing strategies, particularly the microtransaction model with limited vs. fully free play. This particular strategy has proven effective in industry; however, to date there has been no research effort to identify the optimal amount of limitation or the optimal price charged for the removal of this limitation.

5.3 Conclusion

This research effort provides a rigorous examination of the pricing of online games and how network externalities impact the pricing of multiplayer games. In considering this problem, this effort has included a wide range of parameters known to be of import to the player base of online games. While considering as many parameters in this study as was done did result in a few limitations, the implications for management and future research are considerable. The rest of this section provides a brief review of what was done in previous chapters and concludes with a few words about online games and gaming.

The first chapter provides an overview of online games and gaming. This review goes through the different classification of games that exist and makes distinctions about what makes these classifications important. In discussing the pricing of online games, it makes note of the industry structure and how games are digital experience goods whose price is a function of the number of people who are willing to buy the game, the amount invested in developing the game, and the level of service provided to the consumer. Chapter 1 concludes with a discussion of how games are currently creating or maintain revenue streams and how these streams of revenue work.

Chapter 2 takes two of these revenue models, single purchase and subscription, and presents two mathematical formulations and their mathematical properties. Both of these models are three period models and have a growth, maturity, and decline phase and revenues which results from the best prices reflect these phases. For each model, a numerical example is provided which illustrates the pricing changes that occur in each.

Building upon the framework in Chapter 2 and the concepts introduced in the literature review, Chapter 3 contains a numerical experiment which tests the sensitivity of the different parameters in the two models. In this experiment we varied C_D, C_P, C_S, α, N, g, λ, and δ with low, medium, and high values. This was done for the single purchase model with different levels of customer growth expectation and compared (where possible) to the subscription model. In stretching the time horizon from three to five periods, we were able to confirm the pricing patterns found in Chapter 2 in that a best strategy is to hold the price low, raise the price to capitalize on network externalities and their effects on the previous period's sales, and then lower the price again. The chapter concludes with a series of implications about game pricing and recommendations for management. We point to three important conclusions from this chapter. Cash starved publishers should follow a single purchase pricing strategy as it provides more revenue in the early periods. Second, if customers believe that growth will be low but the publisher believes that customers are wrong and that growth will be high, then the company should follow a subscription pricing strategy. Finally, when a publisher is using a subscription strategy, they should oscillate the price of subscriptions periodically to increase utility based on network externalities and then price to capitalize on this increased utility.

Chapter 4 takes the implications about pricing from the previous chapter and builds an agent based modeling simulation in order to examine the different pricing models in greater detail. Four different pricing strategies (fixed price, revenue seeking, and two types of oscillation) are tested for each pricing model. By varying a wide range of parameters and tracking the performance of the game over time, we were able to conclude the chapter with several additional implications and recommendations for management. In particular, we note that a game publisher who is uncertain about the consumer population's preferences should use either a revenue seeking single purchase strategy or an oscillating subscription strategy.

To conclude, video games, specifically online multiplayer games, offer considerable revenue and research potential. Games are unique in that they have proven to be resilient in the face of adverse economic conditions providing a needed escape, however temporary, for their players. It is the expressed wish of the authors that both researchers and practitioners in industry find this research to be both informative and useful in their future endeavors.

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