BLOCKBUSTER EMERGENCE IN ENTERTAINMENT PLATFORM MARKETS: MODELING THE HISTORY OF THE VIDEO GAME INDUSTRY IN NORTH AMERICA.

by

E. André L'Huillier
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Committee:

______________________	Dr. Robert Axtell, Dissertation Director
______________________	Dr. Marshall Van Alstyne, Committee Member
______________________	Dr. William G. Kennedy, Committee Member
______________________	Dr. Eduardo López, Committee Member
______________________	Dr. Jason Kinser, Acting Department Chair
______________________	Dr. Donna M. Fox, Associate Dean, Office of Student Affairs & Special Programs, College of Science
______________________	Dr. Peggy Agouris, Dean, College of Science

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George Mason University
Fairfax, VA

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By

E. André L'Huillier
Master of Arts
Universidad Adolfo Ibañez, 2012
Bachelor of Arts
Universidad Adolfo Ibañez, 2012

Director: Dr. Robert Axtell, Professor
Department of Computational and Data Sciences

Spring 2019
George Mason University
Fairfax, VA

Dedication

To Mom, Dad, Popi, Fer, and the rest of the pack.
And to every single misfit that pushed video games towards the best of our humanity.

Acknowledgments

I would like to thank the following people who made this possible, with special consideration for Professor Robert Axtell, Professor Marshall Van Alstyne, Professor William Kennedy, Professor Eduardo Lopez, Professor Ariel Quezada, Professor Pablo Caceres, Prof Len Nichols, and Prof Makoto Mizuno. Additionally thanks to Professor Yuhsuke Koyama for access to his new book on the history of the Japanese video game industry.

Table of Contents

List of Tables

List of Figures

Abstract

BLOCKBUSTER EMERGENCE IN ENTERTAINMENT PLATFORM MARKETS.

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Dissertation Director: Dr. Robert Axtell

Entertainment markets are typically dominated by blockbusters; which are characterized for being highly popular and financially successful over a vast majority of failures. Today, the entertainment industry has shifted into a platform model, where a similar concentration occurs. The expanding and disruptive placement of multi-sided business organization has modified many cultural markets, reshaping the way products are created, delivered, and consumed. Nevertheless, entertainment platforms still depend heavily on the existence of blockbusters. I study the history of video game industry with particular attention to the life cycle of platforms and blockbuster emergence. After an empirical analysis of the home console market and a literature review of its history, an agent-based model of the video game market is presented. The model aims to represent the complex behavior of the market's heterogeneous actors. The design is based on platform economics, diffusion through social networks, and social influence; with an emphasis in decision making under high uncertainty. Results of the model successfully reproduce the main dynamics of the market in a simple behavioral representation. The simulation experiments indicate that peer influence in a multi-sided organization is sufficient to reproduce the industry's life-cycles, its high concentration, and extreme uncertainty. Furthermore, results of the model display the combined effect of promotion and word of mouth; particularly on how mass promotion provides an

increment in expectation while the tipping force of critical mass depends on social influence. Although the model is able to reproduce the emergence of blockbusters and market concentration in a completely uncertain market, the rule-based nature of its structure allows for future experiments that consider installed base factors, quality, or asymmetries in market power. After the initial results of the base model, a series of extensions are presented to address additional issues of blockbuster formation in entertainment platforms. The extensions focus in the role of market segmentation in quality perception, the effect of uncertainty and consumer perception, and finally, an exploration on basic aspects of platform management. These extensions also contribute to support the use of computational models to address theoretical and practical scenarios for the understanding of entertainment platforms. Results for market composition of consumer preferences and product features presents the complex interaction between sub-groups in the formation of positive expectations and market concentration; where partial diversity of games properties is better than its extremes (i.e. fully heterogeneous or identical). Results on consumer perception experiments also provide evidence of a non-linear effect on adoption and market behavior; with higher perception consumers are able to discriminate earlier without the generation of sufficient hype to form blockbusters or platform participation. Finally, the platform management section goes through matters of time of release, multi-homing, and a price structure prototype. In general, results on these extensions present an important effect of externalities among platforms operations (e.g. the mutual hype generation when consumers multi-home or platforms release at closer dates). Future research on entertainment platforms should consider an empirical approach to describe preference and product heterogeneity, which may further inquire in a critical review of quality in markets with high uncertainty. Finally, the insights of the model are useful for the study of other markets beyond the video games or the entertainment business. The insights provided and the model's framework are relevant to any multi-sided system that sees a dominant herd behavior based in decision uncertainty like social media or platforms for collective action.

Chapter 1: The Video Game Industry.

1.1 Introduction to game markets.

Among the developments of media during the XX century we find many breakthroughs related to the digital revolution. Not long after we began questioning the effects of information technology in our economies, media, culture, and politics [McLuhan, 1964, Postman, 1985, McGinniss, 1988], we were already engaging in the digital alternatives that are fundamental to our society today. As we realize how much we depend on digital structure, platforms, social media, and artificial intelligence, the nature of its effects becomes a discussion of increasing relevance [McAfee and Brynjolfsson, 2017]. Between the many aspects of human activity, games where also affected by the information revolution. It wasn't long after the appearance of the microcomputer, that big arcade machines could be found in restaurants, bars, or entertainment venues [Kent, 2001, Koyama, 2018]. As the market developed with microprocessors, new game companies pushed the limits of technology towards smaller devices that appeared in living rooms, carry-on, and even in our watches. From the first monochrome display of interactive dots in 1971, up to the immersive high definition virtual reality available today, the industry has grown in complexity beyond technological advances. Take for example the 350 thousand units sold by the first home console in 1972 (Magnavox Odyssey) and the almost 140 million units sold so far by the latest home console generation with three competitors [VGChartz, 2018]. What is most impressive, is the development of a complex market behind these numbers; the Odyssey only had 28 games developed (all of them produced in-house) while the latest generation has thousands of third-party games published by hundreds of firms that support a larger amount of separated game developer firms [Zackariasson and Wilson, 2012]. The consumer side has also grown to an estimated population of more than 2 billion gamers (meaning that one in four individuals play games worldwide [NewZoo, 2018]) with an increasing diversity on participation, preferences, and communities. Even though home console is an important part of the industry, today it only generates slightly more than 34% of the industry's US$137.9 Bn. annual revenue. Thus, growth in the last 45 years is not completely captured by the development of this sector as many others have provided major contributions (i.e. PC, hand-held, arcade, mobile, and web based games [Kerr, 2016]). Particularly, the penetration of mobile devices revolutionized this sector and enabled a new open platform for game development, reducing the costs of production and consumption. Until 2018, this emergent sector gained more than half of the market's total annual revenue with US$70.3 Bn. From that total, US$56.4 Bn. come from phones exclusively; making mobile phone gaming alone a larger industry than cinema box office, music, or radio broadcasts. This transition over mobile is part of a general shift towards digital platforms in the last 10 years. Before this, platform competition was driven by developing superior hardware and owning the most attractive game title copyrights. The scope of this chapter is set on the home console sector, specifically between the third and seventh generation of the market.

The home console business is organized in a multi-sided market, where game publishers and developers may offer their goods to consumers thanks to console platforms. Although the definition of platform goes beyond a particular discipline, Eisenmann, Parker, and Van Alstyne offer a concise definition of platform in the organizational and economic sense. They define multi-sided markets as products or services that provide the infrastructure and rules that facilitate transactions between two different groups [Eisenmann et al., 2006]. Firms like Nintendo, Sony, and Microsoft offer hardware devices and licensed agreements to provide a portfolio of games onto the market. This platform business is based on hardware that allows compatible software to be purchased by consumers. Beyond the technical aspects that facilitate development for the platform, the console business depends on the management of publishers and gamers participation. The complexities of platform management have proven to be a challenge for traditional business wisdom, as the non-linear interaction between the incumbent sides requires a different approach. As such, home console has its particular business model to address these challenges [Rochet and Tirole, 2003, Evans, 2011, Hagiu and Herman, 2013]. On the side of consumers, managers maximize the incentives to adopt their platform by offering the lowest price of entry possible. This usually means offering a console price close to marginal cost [Nichols, 2014]. Publishers, on the other hand, will have their access restricted as the manager attempts to optimize the market value of the platform. The role of licenses goes beyond quality control, they also consider optimal logistical operations (e.g. release dates, royalties per volume) and the indirect effects the new title will generate on the platform (e.g. negotiating exclusive rights of a new promising title contributes to securing console sales). Achieving critical mass on participation of any side (which can be only a bunch of high profile publishers or a substantial amount of consumers) usually translates into getting a large market share, if not all of it [Evans, 2011, Evans and Schmalensee, 2016, Parker et al., 2017]. As commonly seen during the 80's and early 90's, if the console does not gain sufficient participation critical mass, it usually flops out of the market. On the other hand, if it manages to do it uncontested, then there is little to no chance for a new competitor to enter in the short term. Thus, manufacturers are pressured to immediately release a competing hardware when another firm already has an active console. Consoles that have been released with similar technological features and game titles have been categorized into classes or generations. Platform competition is usually bounded within this generations where ultimately one or two firms tend to control the market. Although this phenomenon has shifted towards a 'winner-takes-most' distribution of platform market shares, the publisher side presents an increase on concentration. The high uncertainty of making a profit with consoles and games is not only a property of the industrial organization of video games, it is also a property of entertainment markets in general [DiMaggio, 1977, Elberse, 2013]. The same extreme uncertainty seen in Hollywood and studied by Arthur De Vany [De Vany, 2004] is present in other business like music and book publishing. Under a sociological perspective, this behavior is reasonable to expect in a cultural market. Here, production implies the use of symbols and other ambiguous traits that need to be communicated with an increasingly diversifying audience [Keuschnigg, 2015].

This ultimately favors a general product that may connect with this diverse audiences, while consumers increasingly depend on indirect sources of information to evaluate the product. On an economical perspective is important to consider that this condition of product features are basically experience goods [Nelson, 1970]. Meaning that in contrast to the usual good where product properties are knowable (referenced as search goods, as its evaluation depends on the cost of searching information), evaluations on experience goods are only possible after they have been consumed it. Thus, being under a sociological or an economist point of view, uncertainty is an important aspect of the market's behavior as it affects the behavior of producers and consumers.

Yuhsuke Koyama [Koyama, 2018] has proposed four definitions or sub-fields for the analysis of video game history. The following dissertation approaches this platform market history through two of the four main scopes: **a) social history**: focusing on the consumer's heterogeneity, decision making, social influence, and overall diffusion of games and console platforms, and **b) industrial history**: putting attention to the market organization, life-cycle dynamics, influence of media, and the indirect network effects between consumer and developer behavior. In the following dissertation, I go through an empirical analysis of the home console market to study its history under these categories. I take the history of this market as a case study of an entertainment platform industry, with an emphasis in market concentration and extreme uncertainty. After a survey on the industry's history and relevant literature, I propose an agent-based model (ABM) to describe these dynamics and further inquire on its behavior. ABMs have become an important tool to study complex systems [Epstein and Axtell, 1996, Miller and Page, 2007, Cioffi-Revilla, 2014]. The use of ABMs helps to overcome issues of traditional models in diffusion, consumer behavior, and platform economics as they enable the inclusion of heterogeneity and heuristic behavior to the incumbent actors. Additionally, the agent-based simulation temporal dynamics enables a different approach to study specific dynamics like the 'launching problem' [Parker et al., 2017], which involves a complex interaction between multiple types of actors, diffusion, and market conditions. The model presented in this dissertation allows the inclusion of assumptions on perfect information and preference homogeneity, while also being able to relax these assumptions to represent multiple actors with asymmetric populations, features (e.g. preferences), and information processing. Although the model is designed to study fundamental behaviors of the video game market, this dissertation addresses the effect of information on the emergence of hits or blockbusters [De Vany, 2004] that is relevant for all content platforms. The purpose of this work is to show how the 'winner-takes-most' and high market concentration dynamics appear when products' uncertainty is high. Particularly, when consumers recur to peers to gather information. The model shows how modeling platform organization and social influence is sufficient to explain the volatility and concentration of this entertainment industry, while also displaying the effects and consequences of its multi-sided nature. Along with the model, the calibration and sensitivity analysis of social influence over platform competition is presented. For the purpose of this paper, social influence is understood under the social psychology and opinion dynamics literature [Ross et al., 2011, Acemoglu and Ozdaglar, 2011]. More specifically, the focus of social influence is set on attitudinal changes based on peer-to-peer interactions and mass media. Under the scope of a multi-sided organization, these effects are considered to be meaningful in the process of platform and game software adoption.

1.1.1 Information, cultural markets, and experience goods.

As we have discussed, the condition of entertainment goods fills the market with uncertainty and necessity of finding valid information. One of the typical behaviors of decision under uncertainty is imitation, conformity, or gaining more information from a trustworthy source.

To recognize the direct effect of one individual upon another individual or group, it is important to include the vast study of influence within social psychology [Ross et al., 2011], information economics [Bikhchandani et al., 1992], or opinion dynamics [Acemoglu and Ozdaglar, 2011].

Another behavior relevant to the blockbuster formation is the one associated with information cascade decision making. Bikhchandani, Hirshleifer, and Welch [Bikhchandani et al., 1992, Bikhchandani et al., 2008] address the phenomenon of decision making under uncertainty and propose a model of information diffusion. Although the model considers very simple assumptions (e.g. individuals' make decisions in a serial manner), it can capture the nature of collective decision-making using impartial information and sequenced activation. This mechanism may also explain why an experience good can saturate the market upon release and be evaluated as sub-par retrospectively. A good example are Hollywood movies such as "Pixels", gaining $245 million USD in worldwide box office, having only scored a 17% with the critics, climbing only to a 46% approval among the general audience [RottenTomatoes, 2018]. Bikhchandani even showed how positive cascades (where evaluation is biased towards adoption) may rapidly grow after a small percentage of populations' have decided to adopt [Bikhchandani et al., 1992]. The simple model suggests that when information is limited, the market need only a minimal amount of decisions before triggering a behavior cascade based on the information revealed by those who decided.

The third and broader type of influence is associated with the field of social psychology. Under this perspective, social influence is understood as the way individuals' interactions affect emotion, cognition, and behavior [Ross et al., 2011]. An economist perspective may consider risk-aversion and information cascades as core mechanisms for 'virality' and platform adoption. On the other hand, social psychology would focus on cognitive processes such as conformity or identity theory to evaluate how a consumer affects others' decision-making process. These aspects reveal that not only the amount of adopters matter but also the particular features of who adopts, what is that to be adopted, and context. Meaning that even the moment of the day or the differences between an adopting friend, enemy, or role model may have a significant impact in the decision to adopt. Today, many marketing companies follow this theories and attempt to engage consumers via 'influencers' [Chen et al., 2014] or tailored advertisement. Following Latané's idea of influence strength [Latane, 1981], influencers usually have an advantage as it develops an organic relationship with consumers. Thus, mechanisms of social influence like identity or consistency may appear stronger. Overcoming the assumption of homogeneous relationships (as it is the case for the previous types of influence), allows measuring the effect of information diffusion based on relationship types [Bakshy et al., 2009].

Bikhchandani, Hirshleifer, and Welch [Bikhchandani et al., 1992, Bikhchandani et al., 2008] address the phenomenon of decision making under uncertainty and propose a model of information diffusion. Although the model considers very simple assumptions (e.g. individuals' make decisions in a serial manner), it can capture the nature of collective decision-making using partial information and sequenced activation. This mechanism may also explain why an experience good can saturate the market upon release and be evaluated as sub-par retrospectively. A good example are Hollywood movies such as 'Pixels', gaining US$245 million in worldwide box office, having only scored a 17% with the critics in RottenTomatoes, climbing only to a 46% rating with the audience. Bikhchandani even showed how positive cascades (where evaluation is biased towards adoption) may rapidly grow after a small percentage of populations' have decided to adopt [Bikhchandani et al., 1992].

In social psychology social influence is understood as the way individuals' interactions affect emotion, cognition, and behavior [Cialdini, 1984, Ross et al., 2011]. An economist perspective may consider risk-aversion and information cascades as core mechanisms for 'virality' and platform adoption. On the other hand, social psychology would focus on cognitive processes such as conformity or identity theory to evaluate how a consumer affects others' decision-making process. These aspects reveal that not only the amount of adopters matter but also the particular features of who adopts. Meaning, that the effect of an adopting friend, enemy, or role model will vary greatly from the effect of a stranger's decision. Today, many marketing companies follow this theory and attempt to engage consumers via 'influencers' [Chen et al., 2014]. Following Latané's idea of influence strength [Latane, 1981], this type of actors usually has an advantage as it develops an organic relationship with consumers. Thus, mechanisms of social influence like identity or consistency may appear stronger. Overcoming the assumption of homogeneous relationships seen in the previously mentioned types of influence (e.g. Bikhchandani's information cascades), allows measuring the effect of information diffusion based on relationship types [Bakshy et al., 2009].

Additional to the contributions of social psychology and economics, the field of opinion dynamics has given a robust framework to understand influence dynamics in an empirical and quantitative manner [Acemoglu and Ozdaglar, 2011]. It considers individuals' opinion polarity or attitude and, by particular mechanisms of information diffusion, explains the phenomenon of consensus or polarization.

1.1.2 Uncertainty, multi-sided organization, and the history of the video game industry.

The rise of the platform revolution has disrupted many sectors as they shift the way markets operate [Evans and Schmalensee, 2016, Parker et al., 2017] and have risen to become the largest firms in the last decade. It is not unusual to hear about firms like Amazon, AliBaba, Apple, and Google having an advantage over new and old industries while also affecting our daily lives. Given their disruptive nature, platform industries have been questioned on their market power and their role in complex societies, from antitrust cases [Kopel, 2001] to the management of individuals' privacy [Isaak and Hanna, 2018]. The social impact of these organizations is not a novelty if we consider the nature of multi-sided markets, practically existing since the earliest physical marketplace. Soon after the publications of Rochet, Tirole, and Armstrong [Rochet and Tirole, 2003, Armstrong, 2005], the study of multi-sided markets properties has been addressed by academics, policy makers, and entrepreneurs [Evans, 2011, Parker et al., 2016, Parker et al., 2017, McAfee and Brynjolfsson, 2017]. The relevance of platforms grew as new information technologies enabled this type of organization to be designed and efficiently managed (providing speed, security, and automated curation in matchmaking [Evans and Schmalensee, 2016, Parker et al., 2017]). The challenges of explaining, designing, igniting, and managing a platform business also became apparent with this revolution. Among them, the process of formation and management have been particularly difficult to grasp, including the strategies of launching a new platform and the tendency of leading firms to control the market (i.e. winner-takes-all [Evans, 2011]). The effects of the largest platforms have a wide spectrum; from the controversy on city transportation by Uber to the bankrupcy of staple firms like Sears or Macy's under the siege of Amazon. The entertainment industry hasn't been exempt from platform transformations either. Firms behind YouTube, Spotify, or Netflix, have respectively reshaped television, music, and the movie industry while maintaining fierce dominance as market leaders. Although the platform revolution typically brings high market concentration and uncertainty, both have been a natural aspect of entertainment markets since its beginnings [DiMaggio, 1977]. This market behavior has been prominently studied by economist Arthur De Vany, specifically addressing the extreme uncertainty of Hollywood productions [De Vany, 2004]. Under the premise that 'nobody knows anything' made famous by [Goldman, 1983], De Vany attempts to survey this volatility by focusing on the underlying factors like movie stars or genre classifications. Beyond the movie industry, understanding how specific 'hits' are formed in entertainment and cultural markets has been a topic of high interest [Hirsch, 1972, Bielby and Bielby, 1994, Salganik et al., 2006, Bikhchandani et al., 2008, Elberse, 2013, Keuschnigg, 2015]. As a cultural market, the entertainment industries have been studied by its products' ambiguous properties [Bielby and Bielby, 1994] and volatility on their performance [Hirsch, 1972]. The features of cultural products are too diverse and difficult to define explicitly, rising the cost to evaluate them for consumers and presenting a challenge for producers when establishing their target audience. This is why producers tend to offer a wide spectrum of products to satisfy different consumer preferences. The cultural market literature that worries about these properties usually focuses on high market concentration [Bielby and Bielby, 1994] and extreme uncertainty [Keuschnigg, 2015] that seems to shape the behavior of these industries [De Vany, 2004]. Understanding the ambiguous properties of entertainment products and the uncertainty of the market has also been studied in the economic literature under the classification of good types (i.e. search, experience, and credence goods [Nelson, 1970, Andersen et al., 1998]). The defining property of these goods is that consumers usually engage in high costs to evaluate their value or utility before purchase [Nelson, 1970, Darby and Karni, 1973, Andersen et al., 1998, Benz, 2007b]. Individuals can evaluate the quality once they acquire or use the product, which provides enough information to consider future purchases [Andersen et al., 1998]. Although uncertainty is presented to consumers, the risk and costs of operation are also transferred to producers as business sees a high volatility on sales performance [Benz, 2007a]. This uncertainty in products, similar to cultural markets, is also accompanied with market concentration. Phillip Nelson began the conversation around goods properties while also mentioning the effects of experience goods on market competition and monopoly behavior [Nelson, 1970].

The video game industry is one of the oldest platform markets in the entertainment business and since its early beginnings managers have addressed the challenge of matching consumer audiences with content developers [Cohen, 1984, Kent, 2001, Sheff, 2011, Zackariasson and Wilson, 2012, Nichols, 2014]. While operating as a platform organization, they have also faced the uncertainty of the cultural properties of their products [Kline et al., 2003]. As many other entertainment markets, the video game market presents extreme uncertainty and high market concentration, which may be explained in part by: having experience goods [Nelson, 1970, Darby and Karni, 1973, Andersen et al., 1998], being a cultural market [DiMaggio, 1977, Keuschnigg, 2015, Bikhchandani et al., 1992], and operating as a multi-sided organization [Rochet and Tirole, 2003, Armstrong, 2005, Parker et al., 2017]. Its history is filled with blockbuster game titles [Elberse, 2013], platforms that win over the market, 'rock-star' publisher firms, and a long tail of unsuccessful attempts to stay in the market. The evolution of the video market can be classified in a series of console hardware life-cycles or generations, which also help define periods of competition between platforms firms [Kemerer et al., 2017b]. Leader firms usually remain successful through the years but every publisher incurs in high risks and its subject to fail. On the side of platform firms, the risks of becoming an unsustainable operation are high as well. Firms like Atari or Sega, who were renowned hardware companies, ceased their platform operations unexpectedly [Kent, 2001]. Even Hiroshi Yamauchi, former CEO and owner of Nintendo, said before the DS platform release: *'If the DS succeeds, we will rise to heaven, but if it fails we will sink* *to hell'* [Constantine, 2018]. In spite of this extreme uncertainty, the industry's growth has escalated in recent years (surpassing other mainstream entertainment industries like cinema and music).

1.1.3 Structure and chapters contents.

The following chapter surveys the social and industrial history of the home console market in North America. Historical references and an empirical analysis is presented along a description of the market's organization and evolution. The purpose is to understand the console generations life-cycle history and to characterize the general behavior of the market. Meaning, to describe consumers, publishers, and platform managers, and the interactions among them. Along this description, we present how platform economics and decision making under uncertainty (i.e. diffusion of innovations, social influence, information cascades) contribute to explain these properties and behaviors. Finally, the objective is to present a concise history of the industry and to define the fundamental parameters to develop a computational model of the home console platform market. After going through the history of video games with a focus in home console devices, we will present the relevant literature on the industry's organization and behavior that are fundamental for the model's design.

1.2 Video Game History

Although many interactive video games have been made before their commercialization, the industrial history of video games began with the release of 'Computer Space'; the first non-mechanical electronic arcade game produced and released in 1971 [Cohen, 1984, Kent, 2001, Nichols, 2014]). Popular recognition of the first video game usually goes to either the 'Pong' arcade machine [Cohen, 1984, Herman, 1997] or the Magnavox Odyssey home console [Kent, 2001], both released in 1972. This misconception is most likely based on the fact that they were the first arcade and home console system to be a commercial success. During the 70's and early 80's there was a fierce competition for any circulating quarter in the arcades

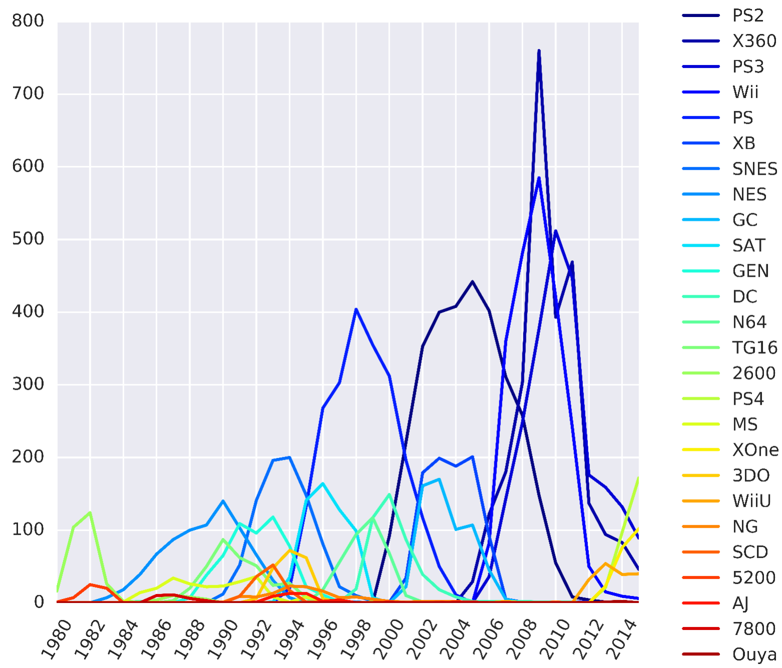

Figure 1.1: Units sold yearly by Home Console platform.

as well as many attempts to be the new households' entertainment device [Watkins, 1984]. Initially, arcades created a new consumer base with more advanced technology and therefore higher technical quality. Appended to this new consumer base, the most successful intellectual properties (IPs) like 'Space Invaders' would be ported to home console with a lower processing and graphical rendition. This period was marked by the birth of the two global leaders; Japan and the United States [Watkins, 1984]. The first console with third-party developers was released by Atari in 1976 [Cohen, 1984] and ever since the industry has dealt with several generations of multi-sided competition [Kent, 2001, Kline et al., 2003, Sheff, 2011, Zackariasson and Wilson, 2012]. This format marked the beginning of the second generation of gaming devices and attracted the attention of large companies like Warner Brothers, which invested and managed Atari's notoriously successful operations. But the management of this new market presented challenges for Warner Brothers business style and they were ultimately questioned for their contribution on the market's crash in 1983

[Kent, 2001]. In 1985, Nintendo brought back consumers and retailers trust with the 'NES' platform that was already successful in Japan. During this third generation, the Japanese company had almost complete control on game hardware (i.e. highest HHI, see Table 1.1) and faced legal actions for antitrust issues and its monopsony behavior [Sheff, 2011]. Figure 1.1 shows the units sold by year per platform, where platforms are ordered by sales starting with the PlayStation 2 (PS2). The Figure shows how platform competition increased at the end of the 80's, which was majorly contested between Nintendo and Sega. The next decade would bring many changes with the advent of the Internet and even cheaper computers; arcade almost disappeared and the adoption of CD-Rom paved the entry of Sony's PlayStation (PS) as a new home console competitor (who was followed by Microsoft on the next generation). Although the 'Super NES' peaked as the market leader in 1993, it was the PS who won the 90's market. Entering the new millennium Sega declared that it would stop its platform operations while Microsoft was taking part in the market. Once again, the transition to the new decade favored Sony, who dominated the console market with the PS2. Most interesting, the seventh generation (between 2007 and 2013) shows a weaker concentration of the market marked by a seemingly stable competition between Nintendo, Sony, and Microsoft. This distance from the 'winner-takes-most' behavior may be explained by the decreased relevance of hardware platforms as multi-homing grew between them and new digital alternatives like PC or mobile phones platforms [Kemerer et al., 2017b].

During the history of video games there has been a fair amount of markets regionalization. Among the most active regions we have North America (mostly the U.S.), Japan, and Europe; leaving behind developing countries with a smaller consumer participation and almost an in-existent production. This division was particularly true in the early years, where the U.S. and Japan were leaders in hardware and software development. In the eastern country, electro-mechanical arcades welcomed electronic video machines while some companies attempted to follow the home 'Pong' craze of the U.S. [Koyama, 2018]. Although their interest was put in domestic markets, Japanese firms looked upon the west for new

Table 1.1: Estimated revenue and market concentration by generations.

Generation	Years	Revenue (2018 prices)	HHI	Market leaders
I	1972-1977	N/A	N/A	Atari, Odyssey
II	1977-1982	US$0.86 Bn	3281	Atari, Intellivision
III	1983-1989	US$ 2.76 Bn	7467	Nintendo
IV	1989-1994	N/A	4867	Nintendo, Sega
V	1994-2001	US$7.98 Bn	4494	Sony, Nintendo
VI	2001-2006	US$19.7 Bn	3093	Sony, Microsoft
VII	2007-2013	US$52.8 Bn	3476*	Nintendo, Sony
VIII	2014-Present	US$137.9 Bn	3417*	Sony, Microsoft

* Estimated using [VGChartz, 2018] hardware unit sales.

business opportunities. The unexploited potential of North American market wasn't unknown for local entrepreneurs and so arcades were filled with game machines coming from eastern and western developers. Meanwhile, once it gained enough momentum, the home console was fiercely conquered by Atari with little to no resistance. The operations to gain their own local markets by United States and Japanese companies left an open opportunity for exploration in Europe. With a weak presence of home consoles, many non-dedicated personal or home computers like the Commodore 64 appeared as gaming alternatives until a late effort to gain the European market during the 80's [Hayes and Dinsey, 1996, Bagnall, 2016]. Atari was by far the most successful company, making themselves a referent of video games in general. In 1983 the market unexpectedly crashed leaving Atari out of operations and almost all consumers and retailers with little to no trust over game quality. Although this affected business worldwide, the impact was most notorious in the U.S. The relative healthy Japanese economy and the already established domestic game market allowed the development of new products. Meanwhile, North American stores only offered old machines at clearance discounts. It was Nintendo that reignited the U.S. market on 1985 with a western design of their Famicom platform (1983). As a sole competitor with a significant gap in technology (compared with pre-crash hardware), Nintendo began a video game empire that is questionable as a monopoly on the consumer side and without a doubt a monopsony over game software developers. During this time the personal computer also ran as an open platform for games, many famous companies and IPs that are still relevant today came from this sector (i.e. Sim City, Doom). Although PC was available since the early 80's, it wasn't until the late period of this decade that games would become widely adopted and produced. The next decade would bring many changes with the advent of the Internet and cheaper computers; arcade almost disappeared and the CD-Rom paved the entry of Sony as a new home console competitor (who was followed by Microsoft on the next generation). Entering the new millennium, Sega (one of the major hardware companies until that date) declared that it would stop its platform operations. At this time, the most profitable sectors were home console, PC, and hand-held. The latter are portable versions of the home console that operate under the same business model. Nintendo was the first to release this type of device and has kept the largest share on the market until today. Although Internet and PC access was common during the 90's, it was not until the mid 2000's that the game market felt a shift towards digital platforms. In 2008 the new mobile phone and PC based platforms were established by entities like Apple and Steam respectively. The advantages of digital distribution, coordination, promotion, and the reduction of entry fees made it a better approach than traditional hardware platforms. Usually, consumers have already paid for the hardware (either PC or mobile phone) and the standardized technology of these platforms makes it easier for developers to produce games (e.g. most platforms run under iOS, Android, or Windows OS).

The general differences between the market regions is important to understand the evolution of home console history. Taking them into consideration allows to get perspective on the particular properties of the North American market. Actors involved in this industry mostly operate as an entertainment business, which is mostly centered on catering audiences with cultural products. Although this goods are highly ambiguous, they are constrained by collective cultural traits and economic conditions. Their success in the market is sensible to conditions like cultural values or consumer preferences. Take for example the total sales

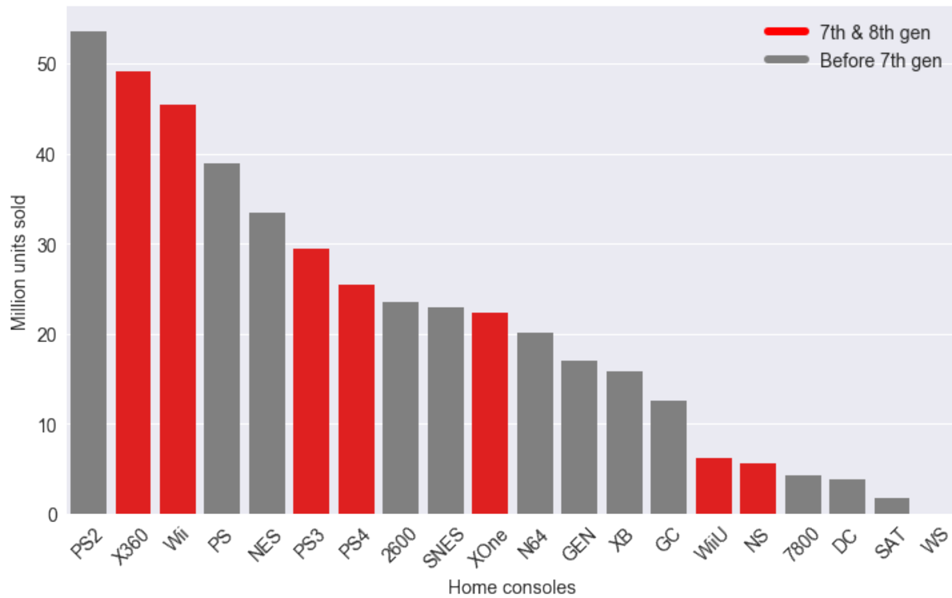

Figure 1.2: Platform sales rank in North America.

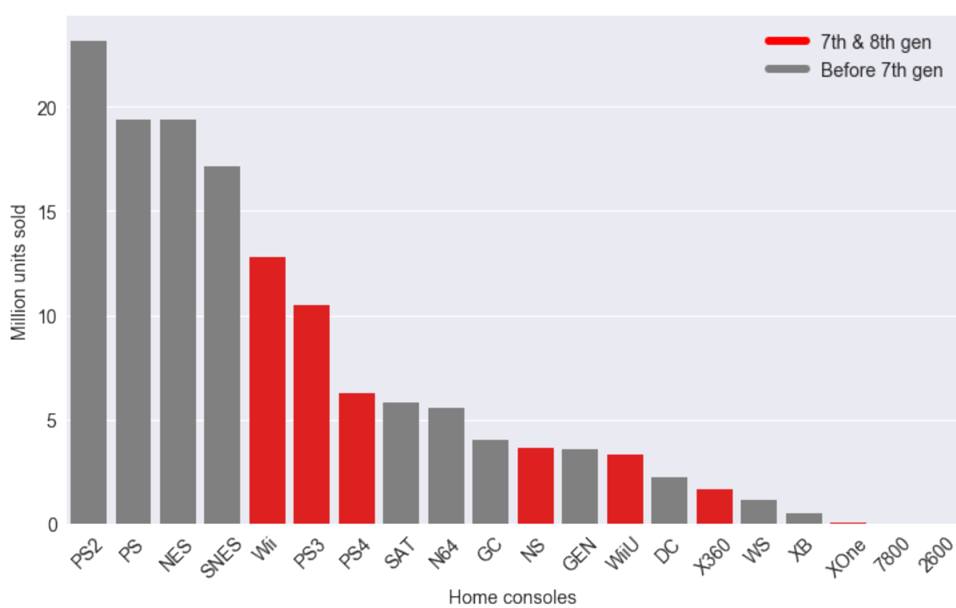

Figure 1.3: Platform sales rank in Japan.

distribution of platforms in North America's home console history (Figure 1.2). Platforms released on the last two generations (7th and 8th) are shown in red and those in grey represent the ones released before this. One of the important differences of the North American market is its relative preference for the Microsoft platform. Although the Wii was a success overall, in North America the Xbox 360 did better than both their competitors. So far, the latest generation has seen the PlayStation 4 barely above the XOne. The Figure also permits to compare the long run impact some platforms like the 'NES' (3rd gen) and the 'PlayStation' (5th gen). When compared with platform sales in Japan (Figure 1.3), we see how the shape of sales rank changes immediately. Japan does not only present a more concentrated market, it also does so by highly preferring national products. As seen in the Figure, the history of this region has been marked by the competition between Nintendo and Sony. These platforms understand their national audience and license thousands of games that are only meant to be played by Japanese gamers. In Figure 1.3 we also appreciate how the newest platforms are relatively weaker in the region, which is known as one of the leaders in the transition towards mobile. Major intellectual properties like Super Mario Bros. and Final Fantasy are already hitting the mobile market. Although a cultural bias may be the reason for this market concentration, it is also possible to consider that the relatively close society of Japan contributes to its generation. Diffusion of any innovation may perceive a faster adoption in an homogeneous and highly connected community. If we consider we are talking about platforms, this effect could be even more strong given the relevance of network effects.

The outcomes of European platform history appears in Figure 1.4. As stated before, the home console industry had a late entry into this region, this is evident on the low impact of older consoles like the Nintendo System (NES) or the Super Nintendo (SNES). This was reversed by the notorious entrance of Sony in the mid 90's. The PlayStation and its successor were massively distributed and still lead the sales rank. Furthermore, the European markets favour Sony over Microsoft in all generations. The composition of a

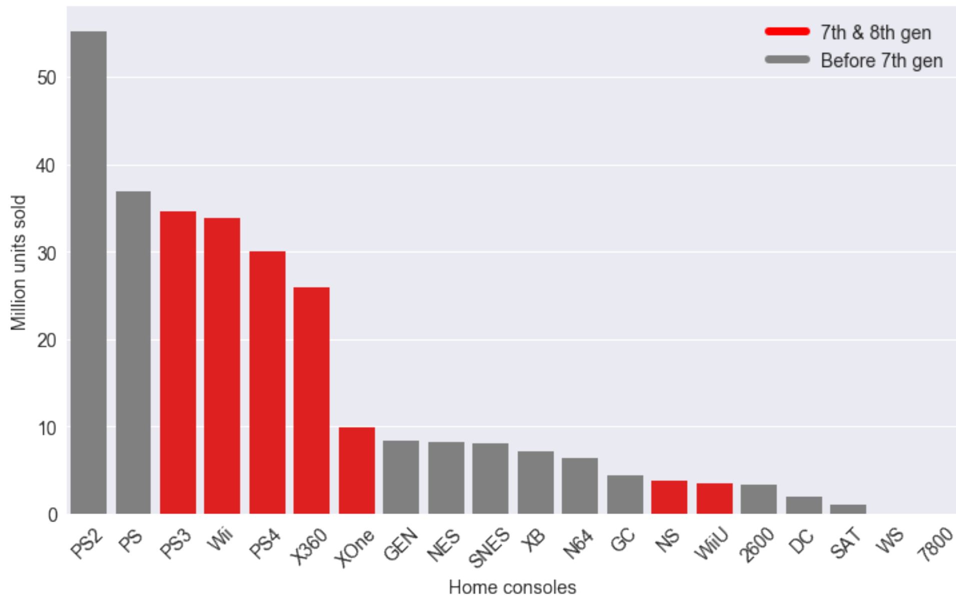

Figure 1.4: Platform sales rank in Europe.

'winner-takes-most' competition is clear if we compare the 5th generation (i.e. PlayStation 2 (PS2), Xbox (XB), and the GameCube (GC)) with the latest complete life-cycle of the 6th generation (i.e. PlayStation 3 (PS3), WII, and the Xbox 360 (X360)). Nevertheless, the PlayStation 4 (PS4) leads the market over the Xbox One (XOne), the WiiU, and the Nintendo Switch (NS) on the current generation. This is also true in Japan, where there has been an historical preference for Sony. What is interesting, is that the PS4 is taking over in North America as well. As of mid 2018, the PlayStation 4 is a strong leader against the rising Nintendo's NS and Microsoft's XOne. The remarking difference appeals to older generations with characterized 'winner-takes-all' behavior. Although Sony is not taking control, it is still an example of how significantly uneven market shares may emerge in this market.

After this revision of total sales per region, it is possible to assess that the North American home console market has seen a larger volume of units sold, it has been more competitive, and has seen more platforms go through their respective generation life-cycle.

The following section presents broad details on the evolution of the home console industry through each generation.

1.2.1 History of the Home Console Industry by Platform Generation.

Following the competition analysis frame of Kemerer [Kemerer et al., 2017b], we decided to use the market classifications of console generations to define competition. This facilitates the study of the winner-takes-most phenomena and allows a comparison of platform life-cycles between the different eras. Thus, the following review of the industry history is structured by these categories. The general consensus and hardware components define the periods of each category as already described in Table 1.1, which also presents the main competitors for every given period. The rise and fall of the leader firms and other important actors is far more rich and complicated than this simple reduction of its history. Below, we go through a brief history of the home console industry since its beginnings until the digitization of the market.

The First Generation: Before Platform Organization.

The release of the first commercial arcade machines and the 'Pong' home consoles in 1972 marked the beginning of the first generation on the video game industry. With a wide variety of hardware components (analog and digital), this era and the next were defined by exploration and several attempts to enter the market. The majority of products tried to capitalize on the hype around 'Pong'. The Magnavox Odyssey pioneered into the home console and it presented similar mechanics to pong but with a variety of different games. This console was the brainchild of Ralph Baer, recognized as the father of the electronic game industry. Baer, with the financial and operation support of Sanders Associates, managed to release his 'brown box' project into a commercial console which was allegedly copied by Nolan Bushnell, founder of Atari and co-creator of the 'Pong' arcade machine. Although Baer's system kick started the industry they couldn't compete against Bushnell's company.

Atari's popularity put them in a position were its brand was a synonym of video games. Its success was not only in the arcade sector but it also captured an important household consumer base with their own version of the pong home console. Thus, they had an advantageous position to develop the new 'next big thing' and with the financial and corporate support of Warner Brothers they pursued the development of the Atari VCS or 2600.

The Second Generation: The Golden Age.

Although Bushnell would later regret his relationship with Warner Brothers, their assistance was fundamental to the success of the Atari 2600. For the first time, the system considered a platform design, meaning it not only catered to gamers but also to third party game developers. This allowed to provide a wide diversity of titles that made the console more appealing to consumers and encouraged the participation of new talents. The inclusion of arcade hits like 'Pac-Man', 'Space Invaders', 'Asteroids', or 'Breakout', appeared as a convenient and safe alternative. As Atari grew in notoriety and revenue, there was over 20 different systems and platforms that attempted to enter the market. Between those who managed to compete against Atari we have systems like the Fairchild Channel F (Fairchild Semiconductor), Intellivision (Mattel) or the ColecoVision (Connecticut Leather Company). Following Atari's business model, most of them had a console open to third-party development. This was an important incentive to the establishment of new publisher and game developer firms like Activision or Sega. After the entry of the pong consoles and Baer's system, demand began growing stronger for both the coin-operated arcades and home console during the second generation. Particularly, during the period between 1978 and 1982 consumption grew from US$215 million to US$3.7 billion (cite 83s Report). As mentioned, Atari was leading the market with more than 550 games until the crash of 1983. Although the U.S. economic recession on 1981 may have played an important role in this sudden decline in video games sales, it is speculated that the main reason was an abundance of poor quality games. As an experience good, an overwhelming shelf space of sub-par products may easily generate distrust in consumers and by consequence to retailers. After noticing the market growth, Warner Brothers appointed Ray Kassar's to manage the Atari division [Cohen, 1984]. His background and decisions were focused on restraining R&D efforts and investing in sales and marketing. Production speed was accelerated and license contracts were set loose, meaning that some developers would have only a couple of months to design games [Cohen, 1984]. The 'E.T.' game is an exemplary outcome of this strategy, and in some cases it is attributed as the sole responsible for the decline of the market. The game was developed in only 5 months and soon after receiving the negative response from the market Atari decided to dispose most cartridges in the Nevada dessert. The Atari 5200 system was released before the market declined, it aimed to be the next generation of gaming platforms but it was discontinued soon after the crash in 1984. By the end of the second generation, Atari had reduced all operations and most products available in the market were offered at clearance prices.

The Third Generation: Rising Sun.

While in the U.S. History of Nintendo in Japan. As both were the main producers worldwide, Japan gained an advantage that it didn't take long to seize. The Family Computer platform (Famicom), released in Japan on 1983, was one of the most successful platforms of Nintendo. During its 20 years of retail availability it sold 61.91 million units worldwide with almost a third sold only in Japan. It released the same year as Sega's SG-1000, a direct competitor that was overrun by Nintendo. Sega's first platform discontinued in 1985 after selling over 700 thousand units while the Famicom was reaching 7 million consoles in Japan [Koyama, 2018]. Although both companies attempted to capture the U.S. market (cite newspaper), it was Nintendo's domestic business that allowed them to offer a new gaming system with hundreds of high quality titles. In 1985 the Japanese console was released in North America as the Nintendo Entertainment System (NES) together with an array of optional gadgets. The market followed the same situation as in Japan, where Nintendo made over 95% of the revenues. The cultural impact of its commercial success was noticed immediately as the U.S. fell into a Mario craze [Ryan, 2012]. Although the NES lost relevance by the end of the decade, Nintendo kept its position as market leader with the release of the Game Boy hand held and announcement of their home console successor; the Super Nintendo Entertainment System (SNES). As the main actor in the industry, Nintendo was target of several attacks beyond market competition. There were many lawsuits against their copyright uses, corporate practices regarding development licenses, or anti-trust violations [Sheff, 2011]. Regardless of Nintendo's power in hardware and software license control, Sega doubled its efforts to compete in the U.S. market. The direct competitor for the NES was the Master System, a same generation successor of the SG-1000 that suffered the same fate. With some momentum from the its Japanese version, the Sega Genesis marked the beginning of the fourth generation when released in 1989.

The Fourth Generation: Platform Wars.

Between the NES and the Game Boy systems, Nintendo amassed the majority of the U.S. consumer base and had almost monopsonist power over publishers. This is why the Genesis not only appealed to gamers with its impressive graphics and 16-bit microprocessor, it also opened a new market place for previously constrained software developers. Additionally, Nintendo would not be able to respond to this threat until 1991; when they released their own 16-bit system. Although Sega had a strong penetration into home console markets and younger audiences, the two years of advantage in hardware superiority was not enough to change the tides. Nintendo would lose its market power but it would still remain on top. Nevertheless, the market had changed and it offered a new opportunity for consumers and developers to have a platform of choice. At the time, the industry's size and notoriety in public affairs would lead the competition into the famous 'platform wars' [Harris, 2014]. Nintendo's 16-bit system, even with significant delay, was the cornerstone to sustain its brand reputation and consumer loyalty. The Mario mania [Ryan, 2012] endured and the plumber kept his role as the face of video games. The struggle between these companies became a staple of the fourth generation, obscuring the participation of other platforms like NEC's PC Engine, SNK's Neo Geo, the Phillips CD-i, or the Commodore CDTV. All this platforms barely managed to ignite a platform ecosystem. The only exception was the PC Engine (TurboGrafx-16 in western markets) that managed to gain the second place in Japan's 16-bit market. It did so with an impressive user base of approximately 10 million systems sold domestically. While the SNES and Genesis sold around 50 and 34 million units respectively, other consoles barely managed to sell over a million. The competition also extended to the hand held sector. Sega competed against the Game Boy with a full color portable called the Game Gear. The market share distribution was mostly taken by Nintendo with over 118 million units and the success of the 'Tetris' game title. As with home systems, Sega followed with 11 million Game Gears in the market while other companies like NEC's TurboExpress (1.5 million) and the Atari Lynx (0.5 million).

The Fifth Generation: Here comes a new challenger.

The transition between the fourth and fifth generation was gradual until the milestone release of the PlayStation (PS). A 32-bit system with polygon rendition that allowed the possibility to develop games in a 3D environment. It was released by Sony in 1994 in Japan and a year later in North America (as it was the norm with most platforms until the sixth generation). Before the appearance of the PS, there were already some attempts to enter the market of home console gaming by big name companies as Sega, Atari, and 3DO (a massive corporate alliance between LG, AT&T, Panasonic, and Electronic Arts, among others). Only the Sega Saturn would make enough profits to sustain their operations. Even when they managed to sell almost 10 million units sold on the consumer side, their system had a negative reception from developers as the console wasn't competitive for software production. This was palpable in the game's quality and the fact that despite releasing in 1993 they sold 20 million units less than the Nintendo 64 (released in 1996). Even after the release of the PlayStation, there were still many attempts to gain a share of the market. Companies like Fujitsu, Commodore, NEC, Apple, Bandai, and Casio made their way through to only get a glimpse of sunlight before discontinuing their platforms.

During the platform competition of the fifth generation, it was clear that Sony's PlayStation gained the 'winner-that-takes-most' title. The impressive technology developed by Ken Kutaragi's team [Asakura, 2000] took the market by surprise. CD-Rom was taking its toll in the platform wars of media formats, the PlayStation captured this technology to allow larger data size and enabling the use of rich audio and video files. Most importantly, the PS engine allowed to render what appeared to be 3D polygons. Furthermore, the pioneers in Sony had a special consideration over the launching and management of multi-sided markets and made sure that the game creators side was properly catered. Licenses deals were strategically considered and an extra effort was put in assisting developers. A specific team was in charge of documenting and developing new tools for developers, making it increasingly easier to produce games for the PS. They marked their success with a record of over a hundred million consoles in the market, and their success is still noticeable today as Sony is keeps the title of market leader on home console platforms.

Although late to the party, Nintendo managed to capitalize on their brand value and consumer loyalty and rank a second place in market share. The big N would skip the 32-bit microprocessors and the CD-ROM hype to offer a 64-bit version of sharp 3D object renders. Titles like Super Mario 64, Zelda: Ocarina of Time, Smash Brothers, or Mario Party, were all blockbusters developed in-house and played a key role in keeping Nintendo profitable. Beside the case of the Wii (2007), the Japanese company has not been able to regain their role as hardware market leader. This doesn't mean that they have lost market power, as selling many in-house IPs on their own platforms has proven to be a successful business model. The Nintendo 64 sold almost 33 million units worldwide with the mayority of their software sales coming from their own game IPs.

The arcade sector had already been reduced to a minimal expression. During the third generation the symbiosis between arcade and home console was still an important part of the market, but as the next generation made its way the arcades lost relevance against a huge consumer base with electronic entertainment in their own homes. In contrast to Japan, where arcades still operate in most urban centers, the U.S. game industry segmented its audience on children and teenagers. As the urban landscape of U.S. cities require , creating a relative disadvantage compared to their eastern counterpart. By the time of the PlayStation era, arcades were almost in existent.

On another hand, the hand held sector thrived for those who managed to stay on top. There were several attempts and failures in doing so, even from Nintendo itself. The Virtual Boy (VB) released in 1995 and was immediately recognized a failure by Nintendo. Following this unfruitful endeavour were several other efforts like Tiger Electronics's 'Game.com', the Neo Geo Pocket, Sony's PocketStation, Sega's Genesis Nomad, or the WonderSwans systems. All of which fell behind Nintendo's own Game Boy Color, a smaller colored screen successor of the Game Boy. Even with the mishap of the VB, Nintendo kept a profitable business extending the GB product line (which not only offered new games but it was also retroactively compatible with older games).

The Sixth Generation: Three's a charm.

Entering the new millennium the gaming platform business left most of its localized operations. Examples of this global approach are the simultaneous release of platforms around the world or the use of internet connection for online play and distribution. The impact of PlayStation in the previous generation attracted investment from 'old' and new firms on game development. The industry's growth not only captured developers attention but, particularly with Sony's abrupt entry and success, it also signaled a great opportunity to be seized. As the risk involved in platform launching was already common knowledge, the number of new incumbents declined during this time. Nevertheless, the stakes where high and Microsoft decided to follow Sony's steps with the release of their own hardware system. After a few years, the tables had turned to favor Sony and Microsoft as the new market leaders, with Nintendo as a third wheel and Sega being out of the picture.

The sixth generation beginning is marked by the release of the Dreamcast, which is the best hardware that Sega ever released. In its short lifespan of 3 years (compared with its competitors average of 8 years) it managed to sell 9.13 million units [Zackariasson and Wilson, 2012]. With over 600 games released in this short window of time, the Dreamcast appeared to be a strong competitor while outsourced manufacturing limited their pricing ability. In 2001, Sega publicly recognized the ill fate of their system and declared its discontinuation only 3 years after its release. Sega would leave the platform business to concentrate only on publishing game software. The decision showed to be X, considering that they had a well established IP portfolio (e.g. Sonic The Hedgehog). Sega's exit opened a wide space for Microsoft attempt to enter the market and, as Sega retired from the platform market, Bill Gate's company was entering the arena with its Xbox system (which was based on their own DirectX technology).

Xbox was the first North American gaming platform to consolidate and achieve financial success since the Atari 2600. Until now, it has remained competitive with two successors and a vibrant digital platform called the Xbox Live (which consumer base goes beyond hardware consoles as it gathers Xbox and PC users). Although the N64 was left behind with the notorious impact of the PlayStation, Nintendo managed to stay relevant with the release of in-house titles that ranked at the top of the video games billboard. The GameCube released in 2001 and sold 2 million less than the Xbox. The second generation of X consoles compromised Nintendo's position as market leader, leaving them in a third place after the North American newcomer. But the old company didn't lose its relevance in software nor hardware, it was again with the handheld systems that Nintendo kept his foot on the hardware game. This time with a virtually absolute share of the sector, the Game Boy Advance sold over 80 million units worldwide while its main competitor (Nokia's' N-Gage) managed to deliver 3 million systems and other runner-ups like Zodiac's Tapwave, Neo Geo Pocket Color, or the GP32 only achieved sales in the thousands.

PlayStation 2 (PS2), this generation's belle of the ball, released worldwide in 2000. It sold 155 million systems worldwide in its 12-year lifespan. Among its many strengths, one of the decisive advantages of the PS2 is how it 'piggy-rides' the installed base of its predecessor with backward compatibility. The success of the PS was translated in an advantage for the PS2 as potential consumers would immediately appreciate its large game library and previous adopters could keep their games relevant when making the transition.

The Seventh and Eight Generation: Internet age and the decline of the Home Console.

On 2005 Microsoft released the Xbox 360, getting ahead and marking the beginning of the next generation. The impact of this new version wouldn't last too long as the project code-named 'Nintendo Revolution' would be announced, taking the mainstream home console market by storm. A blue ocean strategy appealed to mothers and other members of the family that have been usually close to Nintendo hardware without engaging in playing them. The innovative motion controls were such an important new feature that both titans of the industry, Sony and Microsoft, had to follow through with their own versions of the peripheral. Following its success, Nintendo tried to keep the lead with the early release of the Wii U; establishing a new generation of home consoles. The launching resulted to be a failure for many reasons, but it did shed light into the overall interest in home console. Sales for all platforms decline compared with the previous generation, and the relative boom of online multiplayer and mobile has taken the spotlight. Games like League of Legends or Fortnite for PC and a series of mobile games have lead the gaming conversation during the last generation. Regardless of the platforms and publishers efforts to present high quality games (super AAA) the activity in the format has declined. But this decline affects more the hardware version of platform business than anyone. Digital platforms like Steam are leading with low prices and easy access to games (they even tried to tie the knot with the link device). Following this trend, big publishers are responding against platforms and favoring a direct interaction between the firm and its consumers (i.e. Blizzard, Ubisoft).

Microsoft Live has been developed since the beginning, leaving Microsoft the opportunity to merge its community with a PC based gaming platform.

1.2.2 Industry sectors.

Arcade was the first sector to be commercially successful, although the beginnings of "arcade" parlors started with electro-mechanical games it was with video enabled games that the rise of arcade took off. Cultural icons like Pac-Man or Space Invaders were developed during the peak of the arcade market. PC and home console have been the core of the industry, meaning that most successful franchises and companies have profited the most from this sectors. The most iconic brands and characters have gained notoriety within this sector (Mario, Zelda, Doom, ETC). The home console has gained even more notoriety given that not only games are sold but also has hardware (which initially competed as a toy and now competes a home all-in-one entertainment device). PC games have depended in already distributed platforms like operative systems and hardware components, which allowed them to focus on game development without a restriction on the console components. As home consoles take approximately 7 years to release a complete upgrade, PC had the advantage of adopting the newest computing technology in an annual basis. Since the appearance of internet PC developers have pushed the online feature for their games, today online multiplayer gaming is a central aspect of most high profile projects, which has helped the PC community thrive (with the clear advantage of decreasing costs on high performance chips). Home console is trying to compete in this online landscape, showing a lack of infrastructure and a clear disadvantage against the large installed user base from PC (which is mostly based on cheap PC and the fact that most households require a PC for other activities). A derivative of home console is the hand held sector, whose purpose is to provide the "home gaming experience" in a personal and portable manner. After almost 30 years of success this sector is facing a strong competition from mobile, which would be the PC counterpart of the hand held. Nintendo has dominated this sector since the release of the Nintendo

Game Boy (1989) and now has fused both of their business (hand held and home console) into the Nintendo Switch (2017). This is a clear sign of the disadvantage that both sectors have compared to open platforms like mobile and PC, which now have a digital infrastructure that allows many devices and many companies to publish content in the same market. Mobile has been one of the most growing sector in the last decade, with the consolidation o smart-phones reaching penetration o 90-100% it makes it the perfect platform to connect with a diverse range of audiences from all over the world. But the effect of local markets still has a strong influence in how games perform commercially. Geopolitical differences gains relevance in the size of the game industry, how it organizes, and its particular culture of production and consumption.

To get an idea of how different the market is among its different regions, let us go through a brief description. South American and African gaming industry has been mostly based in the strong presence of global brands with few independent developers that have appeared in the last 10 years. The consumer base is also small and games usually are more expensive by lower demand and higher operation costs. Asia, on the other hand, has been and promises to keep its role as major contributor to the industry, during the 80's and 90's Japan was the innovator in game design and console platforms. Today, 2 out of the 3 major companies in console gaming are Japanese. The fast growth of its continental counterpart is playing a shifting role in the market, China's large consumer base and strong economy has taken them to take a lead role in the video game industry (e.g. Tencent bought League of Legends, a share in Activison Blizzard, and now its competing in Battle Royale genre and Mobile sectors). Europe has a long history of software development, the video game community would have strong roots in PC (Commodore 64) and alternative versions of consoles and games. Although during the 80's and 90's mass market depended in PC-consoles and the big 3, the culture of game design has flowered? in this region (making it one of the most competitive in new formats like mobile). Last but not least, North America has been the center of western game culture since its origins. It generated traction with Atari and then with the success of Nintendo in the 80's, making space for big publisher and developer companies that now compete with the Japanese strongest.

1.2.3 Media reception, stereotypes, and popular culture.

Although video games appear not to be part of the mainstream (besides a handful of particular products/symbols), they have always been an important part of society and markets since the mid-70s. News about their growth and impact don't seem to get old, as if people easily forget about their constant operations. One of many plausible reasons of why video gaming is not part of mainstream culture is the cost of playing. On one side we have the price, with an average of US$300 to own a console and US$60 for access to high production games. On another hand, the effort of playing them also raises the bar with 30 to 60 hours of play time to complete a game, which leaves many uncompleted titles on consumers' shelves given the difficulty on the learning curve. Both conditions elevate the requirements for playing, leaving a consumer base prospect of individuals that have a) disposable income and b) plenty leisure time; two conditions that usually don't go together. For most individuals, these restrictions are a natural limitation to access games leaving younger segments as the best segment. The younger audience may receive disposable income from their tutors while having a lot of spare time. Most associations or stereotypes regarding gamers come from this limited segment although we know that today the average age is 35 years [ESA, 2018]. The stereotype may have a relationship with marketing campaigns that clearly addressed kids and teenagers during the mid 80's and early 90's. As soon as we leave this restriction aside the prospect audience gets larger. Take for example Pong or Pac-Man before the advent of home console (arcade games that required only a quarter to be played) or the widespread adoption of mobile games like Candy Crush or FarmVille in a post-hardware era.

Reception of video games has not only been limited to specific segments until recent years, it has also faced some resistance regarding their possible influence on aggressive or addictive behavior. This type of controversy has stirred since the very beginning and it is still a topic off discussion [Provenzo, 1991].

We have mentioned that video games constitute a cultural market. Thus, similar to popular music bands like The Beatles or movie blockbusters like Star Wars, video games stories, characters, and other contents also diffuse into many communities as a culture or subculture. References to popular culture, particularly of the 80's, cannot dismiss the influence of a wide range of video games.

1.3 Industrial Organization.

1.3.1 Home console as a multi-sided market.

The home console game market is organized as a two-sided market [Rochet and Tirole, 2003, Evans, 2011, Hagiu and Herman, 2013, Parker et al., 2016]. Multi-sided organizations can be defined by markets where actors can directly trade with each other given the assistance of a third party. The platform enables such interaction through the reduction of transaction costs that previously impeded trade between sides. Under this definition, markets where an entity provides an environment, framework, tool, or service that enables trade could be considered to have a platform organization. The relationships created among actors of different sides generate value to those involved through direct and indirect network effects [Evans and Schmalensee, 2017]. Additional value generated by same side interactions are given by direct network effects (e.g. telephone service [Rohlfs, 1974]) while inter-side relationships provide indirect network effects [Rochet and Tirole, 2003]; characterized by an increased platform value for one side given higher participation of the counterpart. In the home console market, direct network effects are evident in the consumer side when individuals may perceive higher value on a platform that is adopted by their peers, as information and game titles may be shared. On the other hand, indirect network effects appear clearly on how software developers participation affects the platform value for consumers and vice versa. It is important to consider that not always more is better, and the curation of particular valuable matches between sides grants the core value of indirect network effects [Evans and Schmalensee, 2017]. Thus, the platform benefits from interactions while all sides benefit directly and indirectly. To maintain strong network effects between the involved sides, managers need to plan their matching operations accordingly. This requires a sufficiently fast and accurate match-making within the platform and a proper balance on side's participation. Excessive or scarce participation on one side may affect the incentives to participate of others. Thus, differentiation of prices and other regulations are fundamental to maintain an efficient encounter between sides [Evans, 2011]. Figure 1.5 illustrates the market composition and the price strategy that managers usually employ in the home console industry. Examples of this market organization can be found in places such as traditional farmers markets and hook-up bars, or their most recent digital alternatives eBay and Tinder. The late success of this model is greatly attributed to the growth of information technology, as it now allows to manage large scale digital platforms where users may interact in a curated, fast, and secure environment [Parker et al., 2017]. This approach revolutionizes the way many mass consumer industries work. In many cases, operations cost and capital investments are focused on matchmaking. Take for example AirBnB, a property renting service that does not own or rent the properties used by consumers and doesn't have any hotel operations. The possibility to gather millions of users, grant ease of access, curate interactions, and maintain a safe environment, has lead many industries towards this digital platform shift. In the particular case of the entertainment industry, the effect of information and communication technologies has taken these markets into offering content platforms and slowly abandoning traditional business models and media. Before proceeding to further describe the home console sector as a multi-sided market, it is important to mention some properties of this type of organization.

Although the different sectors imply distinct business models and organization, the most important ones like home console, hand-held, PC platforms and mobile, are based in a multi-sided market organization. This means that the launching and management of a gaming system requires the proper balance of game developer and consumer participation. Even when the platform had ignited and gained enough critical mass in both sides, gaming platforms would require maintaining the right incentives.

As game production depend heavily on digital technology, the development of hardware and consequently software turned into a cycle of obsolete products. Gaming platforms usually consider an average lifespan of 7 years; a short period that usually consists in an initial phase of ignition (where both developers and consumers need to be persuaded of the platform's advantage), a second stage where both sides may contribute enough to the platform's value requires management of the games portfolio , and a third phase where the platforms is gradually and strategically discontinued to favor the new generation. Although hardware companies need to be constantly developing new devices, the incentives for planned obsolescence usually come from competition rather than a motivation to sell new products.

Entering the competition of game hardware requires a considerable investment along a high risk of failing on platform ignition. On the other hand, those who manage to succeed face the rewards of controlling large shares of the market. This phenomena is present in many platform markets like operative systems, media formats, or social media, and it is known as the 'winner-takes-all' or 'winner-takes-most'. It is particularly generated by the basic nature of platform organization; indirect network effects. By enabling the interaction of two distinct market actors (usually with an asymmetric incentive mechanism or price structure), platforms allow individuals to trade or offer value in an otherwise unfeasible activity. Furthermore, the population size of each of these sides will affect the activity of their counterpart (most men wouldn't find a dating bar attractive if they only allowed one woman to enter). In game systems, the right balance between game titles (based on the amount of participant developers) and consumers is a key factor for a healthy platform. The price structure that maintains this balance in video game platforms is generally achieved by a) pricing consumers barely above marginal cost on hardware while gaining on software titles, and b) asking a license price for developers that is usually paid as a percentage of total title sales.

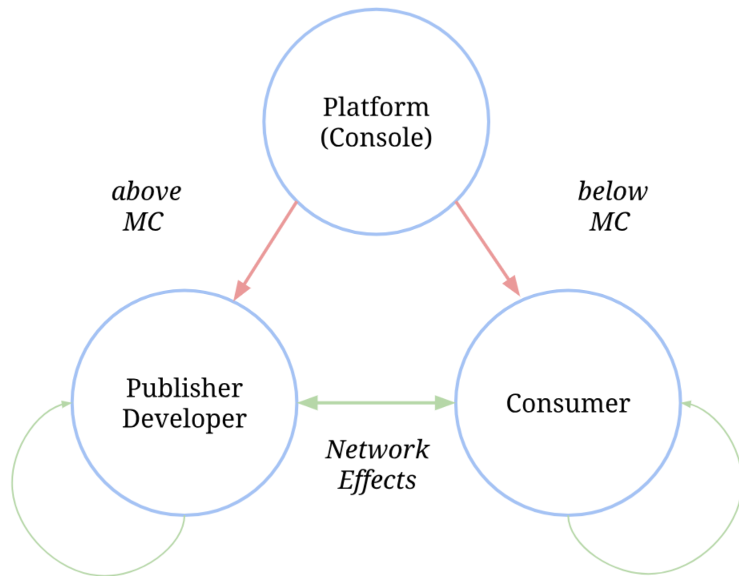

Figure 1.5: Basic Platform Organization for Home Consoles.

1.3.2 Platform Economics.

Platform or multi-sided markets have rapidly gained relevance given their disruptive effects on social organization and sectors like retail and service. The particular structure of platform markets has been one of the fundamental elements to enable the growth of companies such as Google, Amazon, AliBaba, eBay and Facebook, among many others. Since the installment of credit card companies, the development of new platform markets has been thriving and getting attention from business, academia, and even antitrust legislation due to their natural tendency to dominate market share [Evans, 2011,Parker et al., 2016,Rochet and Tirole, 2003]. Although platform markets have existed since early social organizations, the past few years have been witness of a swift growth enabled by the development of digital technologies. The possibility to gather millions of users, grant ease of access, curate interactions, and maintain a safe environment has lead many industries towards this digital platform shift, either as an entrepreneur or simply trying to stay competitive. In the particular case of the entertainment industry, the effect of information and communication technologies has taken these markets of experience goods into adopting platform models (e.g., Netflix, Spotify, YouTube, Steam) and slowly abandoning traditional business models and media.

Organization of multi-sided markets.

The academic study of platform organization has risen since the proposition to consider two-sided markets as a distinct market structure [Evans and Schmalensee, 2016, Armstrong, 2005, Rochet and Tirole, 2003, Parker et al., 2016, Parker and Van Alstyne, 2010]. As it directly impacts information technology industries its relevance has grown beyond scholar grounds, many practitioners and policy makers are getting involved as the platform business model is disrupting traditional industries [McAfee and Brynjolfsson, 2017]. Today, most renowned companies have successfully taken a lead role in their respective markets using a platform business model (e.g. Google, Amazon, AliBaba, Facebook, Uber, and AirBnB among many others).

Platform or multi-sided organizations may be defined by markets where actors can directly trade with each other given the assistance of a third party. This third actor, referenced as the platform, enables such interaction through the reduction of transaction costs that made the trade previously unviable. Under this definition, any market where an entity provides an environment, framework, tool, or service that enables trade could be considered to have a platform organization. The respective sides that interact through the platform have a more flexible definition, particularly when individuals may change roles from supplier to consumer and vice versa. Examples of platform organizations can be found in places such as traditional regulated farmers market and hook-up bars, or their most recent digital alternatives eBay and Tinder. The late success of this model is based on the growing availability of information technology, as it now allows to manage large scale digital platforms where users may interact in a curated, fast, and secure environment. This approach revolutionizes the way many mass consumer industries work. In many cases, operations cost and capital investments are kept at a minimum of secure, fast, and accurate matchmaking operations like AirBnB. A property renting service that does not own or rent their own properties and doesn't have hotel-like operations, they dedicate to properly introduce someone who provides this service to respective consumers.

Economies of scale and Critical mass.

As platforms assets are beyond its own domain, these markets depend on their user base to generate value. Thus, the participation level is key for a platform's success. As with traditional markets, economies of scale are a critical element to consolidate a position among the competition. In a multi-sided market, the larger the community the easier it is to provide more types of services with better quality. Furthermore, following the nature of match-making, the scale of quantity usually goes in hand with a scale of quality; as having more participants allows better match-making. Take for example dating sites, while having more users enables the platform to properly match more and more users, they are also able to look for more specific traits on the users and provide a more curated and tailored match (ultimately providing a higher social welfare). As user base is fundamental to create value, it is important to achieve a minimum amount of individuals to maintain operations that are cost-effective for all sides. This minimum user-base size is referred as critical mass. It is important to say that in platform organizations, success does not fall far from failure. A large user base allows the platform to operate, but it also may be sufficient to lock-in the business as the sole or major competitor over the market. Most of the time staying in the game translates into winning the game [Evans, 2011,Parker et al., 2017]. The all or nothing behavior is sustained given a large enough community, but the mechanism to explode and becoming the market's leader is based on other social behaviors.

Winner-takes all or most.

As mentioned before, achieving critical mass and gaining on network effects do not only allow the provision of a valuable service, it is also key for the platform survival. Once a base threshold of active individuals has been achieved, posterior social influence and network effects may be enough to keep the platform on the top of the competition. As in the case of content formats, social platforms, or operative systems, there is a pattern where those who dominate the market taken most of its market share. But this situation is not enough to appeal over and uncompetitive scenario or anti-trust issues. Even when the contender platform competes against a single company, the situation may turn drastically leaving the former leader company out of the game (e.g. Facebook versus MySpace). Innovation is the tip of competitiveness sword, although it may need far more sharpening that one would expect. Although this is a natural property of platform competition, the pseudo-monopolistic dominion is not the norm in many industries shaped by platform business. As a platform' service may be diverse and address specific communities they can engage with specific segments of a major sector (e.g. Vimeo and Youtube's horizontal differentiation). On the other hand, there is vertical differentiation, when platforms offer advanced features at a price (usually together with free access and basic features). In the worst case, a lack of differentiation may lead to losing the business. In a more positive scenario, it may incentive individuals to adopt several platforms at the same time or, as it called in the literature, to multi-home.

Price-setting and Multi-homing.

To better understand multi-homing in multi-sided markets it is important to consider the challenges of a platform's price structures. Setting the entry price is one of the most challenging aspects of launching a platform. Initially, this cost would reflect the particular advantage of adopting the platform for any side (either consumers or developers) but too much or low of one side can make the whole system collapse. The managers' task is to find the right balance between them via price and user policies. Against traditional approaches, price would not necessarily cover the marginal costs of the operation (at least not for all sides). It is not unusual to have a price structure where one side pays less than the marginal cost, while the other side gets charged more to compensate. Within the video game industry, consumers pay less than the marginal cost of hardware consoles [Evans, 2011, Zackariasson and Wilson, 2012]. They do this to incentivize more individuals on one side to adopt, generating indirect network effects for the other sides. The complexity of the price structure grows if we consider platform competition, where two or more platforms attempt to gather users for each side. Multi-homing of platforms will vary depending on the industry's competitive prices, if entry is relatively cheap it will probably generate some multi-homing behavior. For example, Uber and Lyft are competing platforms with low entry costs (i.e. switching between them only requires a smart-phone application and a free account). On the other hand, markets of operative systems or game consoles require a higher investment and usually do not present multi-homing behavior.

Speed, Security, and Specificity.

Offering platform solution to traditional industries bring new disruptive openings and a fierce competition. But even without competition, to establish a successful platform it is important to meet some baseline requirements. Platforms only provide value or benefit once the transactions gain an advantage compared to other platforms or non-platform interactions. To provide the proper cost-effectiveness in transactions, the platform needs to meet a minimum standard on relevant traits. The fundamental aspects to be considered would be: a) speed, usually speed of engagement with others and service use; b) specificity, how much does a particular match covers the sides' preferences and interests; and c) security, covering from financial to privacy protection. In other words, if your Uber driver takes an hour to arrive, you get a limousine instead of a car, or the vehicle is missing the doors, you would most probably be asking a friend for a ride.

Network effects, information cascades, and social influence.

An interesting aspect of platforms is that the size of operations does not only provide an economy of scale in terms of tailored supply and demand, it also decreases the value of not adopting the dominating platform. As more individuals adopt a platform, the value provided increases non-monotonically. Those who have not adopted usually perceive a lower relative advantage in staying outside of this platform. As discussed before, a platform's creation of value is based on the network effects present in the multi-sided interactions. The case of VHS versus Betamax [Farrell and Klemperer, 2007, Liebowitz and Margolis, 1995] shows a clear example of how not adopting the dominant platform becomes more expensive as the leading format takes more ground on the market. As more people use VHS, network effects on Betamax decrease affecting the value of the format (e.g. lending tapes becomes relatively less convenient than VHS). Network effects can be considered to be direct (i.e. where similar individuals benefit from others' use of the platform) and indirect (i.e. when individuals benefit when another different type of individual uses the platform) [Evans, 2011, Parker et al., 2016]. Depending on the conditions of the market or service, network effects may have a stronger influence on platform adoption. Social platforms such as Facebook have strong network effects as once a critical mass of individuals engage in the platform, most individuals' will benefit from adopting as most their contacts will be there. On the other hand, Uber's platform model does not compel a platform's lock-in (as the cost of switching between Uber and other companies like Lyft is negligible).

Home-console as a Platform Market.

Although many digital entertainment sectors have hopped into the platform model in the past decade, the video game industry has been one of the very earliest successful multi-sided markets. Access to game software has historically been dependent on hardware (e.g., Atari, Nintendo, Sony) (Cite, Manufacturers) and the market has naturally evolved into the platform structure where the console's manufacturer encourages third party software developers to release content on their machine. They do so while also promoting to the consumers' side. Since the release of the Atari 2600, operations of most home and portable consoles had required developers to select a platform before producing any code or design. The last decade has seen a shift in this approach as middle-ware allows for a faster and easier production that may target multiple platforms. This change has been reflected in a transition from a 'winner-takes-all' market, into one where there are few but stable contenders

[Kemerer et al., 2017a].

It is important to say, that although platform organization may be natural for this industry, their digital counterparts are new and already generating pressure. Companies like Sony, Microsoft, and Nintendo are struggling to transform their hardware communities into a digital market. While they still depend on proprietary hardware, firms like Valve and Apple are becoming important players in this new format.

1.3.3 Diffusion of Innovations.

Adoption of home consoles.

To study the process of how a particular product or idea spreads through any social system, we may recur to studies of diffusion of innovation [Rogers, 1962, Valente, 1995]. [Rogers, 1962] defines the basic elements to study the diffusion of any innovation as time, social system, channel and innovation, considering the latter as any product, idea, or habit that is new for the social system. The study of innovation diffusion has helped to understand the penetration process of different innovations into markets and organizations. Thus, it has been an essential framework for marketers and business scholars in general. Understanding the dynamics of adoption is an important element of platform management, this is why it is also a useful to analyze the relative state of a multi-sided organization [Evans, 2011]. Furthermore, the entertainment market also studies and attempts to influence the diffusion of cultural products. Marketing operations related to products such as movies, books and video-games greatly benefit from the generation of expectations before the product's release, or what is commonly mentioned as 'hype'. The efforts to gain adopters before a game's release are common in the video game industry's practices, it is estimated that big productions (referenced as 'AAA') dedicate almost 50% of a production budget for pre-release marketing and advertisement. This practice is particularly concerned to out-perform in the first weekend, to signal a game's financial success and good reception. Although it may seem more extreme in entertainment markets, understanding how information and adoption spreads through the social system is key to make management decisions on product design and promotion. Specifically for platforms, diffusion allows to survey side's participation and respond with a proper strategy to balance it.

The framework proposed by [Rogers, 1962] considered how a specific innovation was adopted through time, which usually is represented in a sinusoidal or 'adoption' curve. The [Bass, 1969] model, that represents this curve, has been a cornerstone to diffusion modeling and it describes the adoption process in terms of internal and external influences. The Bass model is represented in an equation where q is an internal factor representing effects of adopters on non-adopters and external factors like mass media or price discounts are represented by p.

The yearly sales of home consoles between 1980's and 2000's follows the typical diffusion curve. Figure 1.6 shows the normalized diffusion curves of the ignited platforms of these decades. Typically, the early adoption phase occurs in the first two years and on average

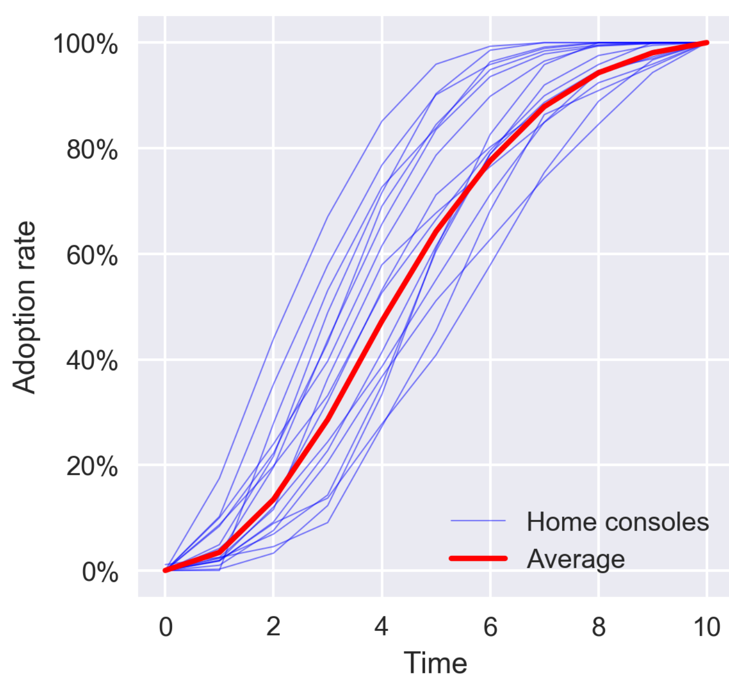

Figure 1.6: Platforms adoption curves and average.

Table 1.2: Fit values of home console adoption using the Bass model.

Console	Year	Units (mil.)	p	q	R^2
2600	1977	24	0.020	0.70	0.99
Famicom	1983	19.3	0.060	0.55	0.98
NES	1985	33.2	0.010	1.00	0.98
Pc Engine	1987	6	0.080	0.60	0.99
Genesis	1988	30.1	0.030	0.55	0.84
Mega Drive	1988	3.5	0.080	0.90	0.98
Super FC	1990	17.1	0.080	0.70	0.99
Super NES	1990	20	0.100	0.80	0.97
PlayStation	1995	102.5	0.050	0.65	0.99
Nintendo 64	1996	34.6	0.080	0.80	0.99
PlayStation 2	2000	153.2	0.040	0.40	0.98
GameCube	2001	21.7	0.150	0.80	0.96
Nintendo DS	2004	156.6	0.035	0.80	0.99
Xbox 360	2005	80.3	0.020	0.70	0.99
PSP	2005	71.4	0.055	0.65	0.99
PlayStation 3	2006	87.3	0.035	0.70	0.99
Wii	2006	102.8	0.050	0.99	0.99
Mean values			0.057	0.722	

reaches saturation in 11.47 years. Although a home console platform may reach beyond 10 years of activity, it takes a lower priority after a new generation appears (on average after 6-7 years). To survey the typical behavior of diffusion in home consoles we compared consoles curves to the Bass model. Results for the corresponding p and q values to fit empirical data with the Bass model are presented in table 1.2. Most consoles have a high r-squared in their similarity, except for Sega's Genesis who presents a slightly different behavior (the diffusion of the Genesis was significantly interrupted by the release of the Super Nintendo). Different from other platforms, the Genesis does not have two inflection points, but three given the disruptive effect of the Super Nintendo [Harris, 2014]. Parameter values indicate the clear relevance of external factors in console adoption. While the mean value of internal forces is 0.057, the q parameter average is 0.722. Thus, according to the Bass model, factors like promotion would better explain the diffusion of the platforms, which is compatible with the marketers' significant investment in advertisement and marketing. Although the simple model allows to accurately fit the empirical data it doesn't help to understand the underlying behaviors of diffusion. Models like this usually divide individuals in categories like early or late adopters, which definition goes beyond the moment of adoption and includes different decision making, risk aversion, and life styles, among others. Thus, this framework does not allow dis-aggregated analysis of individuals or groups as heterogeneous but representative individuals.

The development of an agent based model permits to represent individuals heterogeneity and explicit behavior of adoption [Rand and Rust, 2011]. More than providing a good fit, it allows to test the theory or mental models associated with consumers while constraining their behavior with known facts. The model presented below gives particular emphasis to this behaviors and the resulting collective decision of adoption. Before going into the model details, lets review the home console sector as a platform market and the key aspects to consider for the analysis of hit-making in an entertainment platform.

Publisher adoption.

Here you should put more on the Bass model (Equation) and extend on limitations and use of bottom-up approach.

The same diffusion analysis can be done over publisher participation. Usually, the adoption of any new innovation is studied by individuals and not firms, decisions regarding the selection of a platform are based on expert teams discretion and informed arguments. Still, the adoption of platforms usually a preferential attachment heuristic based on larger consumer base or market's credence on its ability to succeed.

1.4 Evolution of the industry in North America.

Throughout the history of the home console industry in North America there have been several companies that achieved dominance on platforms and game titles [Kent, 2001, Sheff, 2011, Herman, 1997, Goldberg, 2011, Hayes and Dinsey, 1996, Harris, 2014, Rutter and Bryce, 2006, Nichols, 2014, Egenfeldt-Nielsen et al., 2012, Ryan, 2012, Asakura, 2000]. Cases like

Figure 1.7: Publisher monthly releases (from 3rd generation to mid 7th).

Atari, Sega, Nintendo, and Sony, took the role of leaders in a 'winner-takes-all' organization. As generations went by, the platform concentration loosened, . The privileged position of market leader provides several advantages that for the company. Being either a developer in the software sector or a platform firm competing in hardware, the market leader may rapidly become a 'rock-star' compelling other actors to collaborate. This preferential attachment behavior positions the winner in a secure position, where brand value and trust is ensured from consumer and developer sides. Regardless of this advantage, the market scenario is generally volatile. The industry evolves according to innovation disruptions that create fast-paced home-console life cycles. Although new competition could enter and win over the market, defending leaders fight back through install-based effects; such as market's trust or consumer and developer's investments (i.e. purchased consoles and licenses respectively). The leader's endowment of human capital, assets, and large consumer and developer communities, plays an important role in getting an edge on a new generation's competition. These generations usually last 6-7 years on average, while software has an even shorter time window (most revenues come from the first ten weeks).

1.4.1 Generations.

As stated in the section of the industry's history, the definition of platform generations plays an important role in studying its life-cycles. These boundaries help us to define competition through metrics like market-share and delimit the period of the platform active diffusion. Thus, the definition of a 'winner' is dependent on the confines of generations' time-frames [Kemerer et al., 2017b]. To evaluate competition of consoles, we consider this classification as displayed on Table 1.3. We do not include the latest release of Nintendo, which could be defined as a new generation. As competitors have not responded yet with any hardware releases, it would be misleading to consider it a new generation of population one.

The availability of cheaper hardware helped home consoles to replace arcade machines and parlors. Although for some years developers would release their title on both platforms, the business model of arcades required special software and hardware to exploit its format. One of the oldest technological platform rivalries was against the PC. Technology convergence, decreasing production costs, and the penetration rate of home computers for non-gaming activities has favored PC. For a while, the console format allowed for a standard hardware, where consumers could benefit from a one-for-all access to software, unlike PC where hardware was very heterogeneous.

Table 1.3: Game production.

Gen.	Platforms	Games	Units (mil)	Publishers	Developers
II	1	500	N/A	49	93
III	3	1494	414.25	132	348
IV	7	2868	266.12	239	633
V	6	4140	927.32	401	1048
VI	4	5866	1361.04	350	1159
VII	3	5269	3491.1	336	1134
VIII	5	2979	1240.96	477	810
Mean	4.14	3302.28	1283.46	283.42	746.42
St.Dev.	2.03	1938.99	1166.09	151.84	411.09

The core dataset used was extracted from VGChartz [VGChartz, 2018]. Table 1.3 shows the main descriptive statistics for each period.

Gaming platforms usually consider an average lifespan of 7 years; a short period that consists of three major phases: the initial phase of ignition, a second stage of the platform's value consolidation, and a third phase where the platform is gradually and strategically discontinued to favor new technology. Although hardware companies need to be constantly developing new devices, the incentives for planned obsolescence usually comes re-actively, as any innovator pressures the competition.

1.4.2 Console platforms.

Platform activity.

To understand a platform's state it is fundamental to know how much activity it has in all sides, considering how sides affect each other. Understanding the elasticity relative to changes in each side is fundamental. Particularly, when the network effects present in platforms like gaming or music may be highly sensitive to publisher features. Unless a consumer is a very important public figure, the marginal effect of one consumer adopting the platform is relatively insignificant compared to the effects of the major publisher entering or leaving. Regarding the participation of consumers, the quantity of hardware consoles sold reflects the demand and is a fair proxy for adoption. On the software development side, the activity of publishers is reflected in the number of license deals or releases within the platform. Additionally, it is important to consider the distribution of developers among publishers to understand the relative market power of publisher firms. Developers may negotiate directly with the platforms acting as publishers, which is usually done in large developer firm or in independent firms. Thus, the main parameters regarding platform activity would be consumer adoption, publisher adoption, and developer-publisher deals.

The study of a home console platform requires to survey the participation of its main two sides: consumers and publishers. To understand a platform's state it is fundamental to know how large are all sides, with consideration on how sides affect each other. Understanding the elasticity relative to changes in each side is also key. Particularly when the network effects present in platforms like gaming or music may be highly sensitive to publisher features. Unless a consumer is a very important public figure, then the marginal effect of one consumer adopting the platform is relatively insignificant compared to the effects of the major publisher leaving. Regarding the participation of consumers, the quantity of hardware consoles sold reflects the demand and is our best proxy for adoption. On the software development side, we have publishers and developers. The size of the publisher side is seen in the number of license deals or contracts for production and release within the platform. Additionally, it is important to consider the distribution of developers among publishers to understand the relative market power of publisher firms. Developers may negotiate directly with the platforms acting as publishers, which is usually done in large developer firm or in independent firms. Thus, the main parameters regarding platform activity would be consumer adoption, publisher adoption, and developer-publisher deals.

Multi-homing in the console market.

There are many aspects to consider a platform's market power, but one of the critical aspects to evaluate and manage is multi-homing. The change of multi-homing rates between platforms can measure its relative power against direct competition. The amount of multi-homing activity for consumers (i.e. adopting several consoles) or publishers (i.e. releasing the same game in several consoles) defines who may have the upper hand in the market. For example, if all publishers multi-home a certain console then its library becomes irrelevant for the consumer.

Beyond the price structure, console platforms incur to other important incentives like exclusive titles. First-party games (developed by the manufacturer firm) and exclusive third-party licenses form a unique portfolio to compete against other platforms. Although publisher multi-homing is common in the history of home consoles, they usually implied different software for each target device and to develop again from scratch. As middleware technology evolved, the costs of porting the original code has diminished, favoring publisher's multi-homing. Today, most games are released in the major platforms simultaneously.

Platform competition.

Another important aspect to assess competition throughout the platform's life-cycle is the relative market share of platforms and game software. The distribution of sales allows the evaluation of those consoles and titles that dominate the consumer side and most likely have an advantage on the publisher side too. Platform sales distribution is a direct evaluation of the firms' market share. As we know, the 'winner-takes-most' is a natural property of these markets. A detailed analysis of how market share changes and the overall performance of platforms begins from a survey of the distribution of sales or licenses. The game distribution also permits the description of the 'blockbuster' phenomenon in content goods. The establishment of large IPs or brand recognition has an important impact in this market as, brands evolve into mass culture symbols on one hand, and they also get a reputation advantage to signal good quality on these experience goods. Thus, we should consider two additional parameters: platform unit sales and game unit sales distribution.

As mentioned before, one of the key conditions to run a platform business is gaining enough participation of interested sides. In the case of the game industry, the main sides to balance the platform's value are publishers and consumers. The first objective is to launch a platform, as it is possible that a console may not gain sufficient critical mass and flop out of the market. On the other hand, if it manages to do it uncontested, then there is little to no chance for a new competitor to enter in the short term. Manufacturers are pressured to immediately release a competing hardware when another firm already has an active console.

Consoles that have been released with similar technological features and game titles have been categorized into classes called generations [Kemerer et al., 2017a]. To study home console platform competition we need to define its boundaries in time and segment. Generations are a natural classification of competing platform firms where ultimately one or two firms tend to control the market.

The scarce participation of firms in the platform market may be explained by its operation's high costs and risks. Entry to the market of game hardware requires a considerable investment along a high risk of failing on platform ignition. On the other hand, those who manage to succeed, reap the rewards of controlling large shares of the market. This phenomena is present in many platform markets like operative systems, media formats, or social media, and it is known as the 'winner-takes-all' or 'winner-takes-most' [Evans, 2011, Parker et al., 2017, Parker et al., 2016]. Beyond ignition, the main task for platform managers is set on incentives for the proper sides participation. In game systems, the right balance between game titles (based on the amount of participant publishers) and paying customers is the key factor for a healthy platform. The price structure that maintains this balance in video game platforms is generally achieved by a) pricing consumers barely above marginal cost on hardware while gaining on software titles, and b) asking a license price for developers that is usually paid as a percentage of total title sales [Kerr, 2006, Kerr, 2016, Evans, 2011, Nichols, 2014].

It is important to say, that although platform organization may be natural for this industry, their digital counterparts are new and already generating pressure. Companies like Sony, Microsoft, and Nintendo are struggling to transform their hardware communities into a digital market. While they still depend on proprietary hardware, firms like Valve and Apple are becoming important players in this new format.

Platform seasonality.

The period between 1980 and 1990 show the prevalence of almost monopolistic control of firms like Atari (2600) and Nintendo (NES), while the seventh generation portrays a very competitive and synchronized life-cycle for all platforms. Although all this firms were profitable, this period is notorious for the lack of other market entries. It is important to note that platforms and software goods follow a highly seasonal effect, making sales peak in November and December by almost 700% (Figure 1.8). The magnitude of the season's peak appears to be consistently correlated with the performance in previous months. Meaning, that seasonal surges in these months affect proportionally to sales during the year. Different from the monthly time series in Figure 1.8, most data of platform and game unit sales of previous generations is in a yearly scale.

Through the years, the home console shows constant growth peaking in 2009 (when the

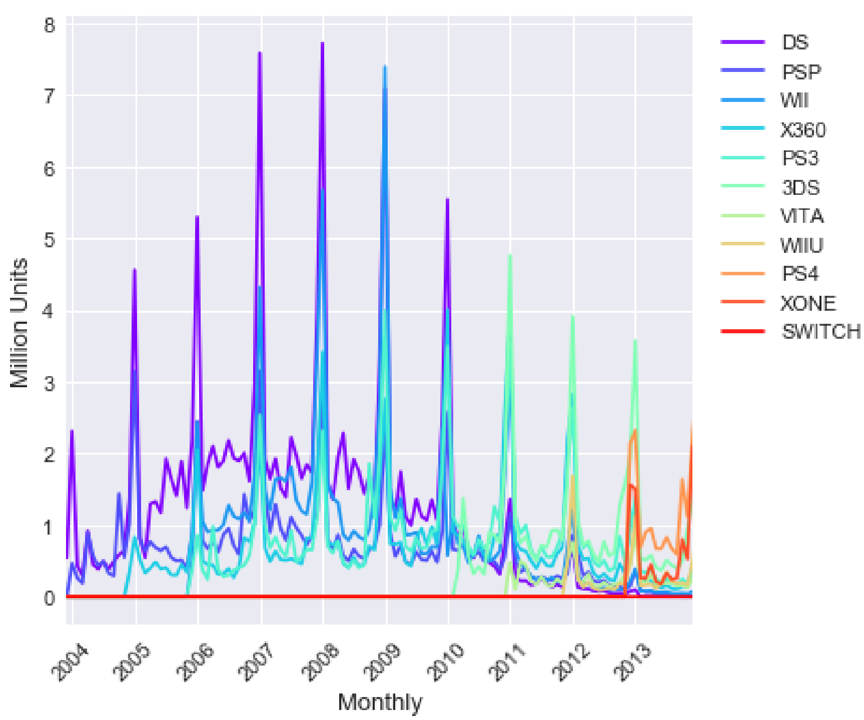

Figure 1.8: Monthly console sales for the North America.

seventh generation was achieving a stability stage). The total amount of games released seems to have peaked one generation before with 5866 games released for game consoles. Table 1.3 shows the amount of platforms, publishers, and developers that formed part of the industry. Although there are some noted acquisitions in the publishers side, this usually happens between large firms. The ratio between developers to publishers has grown from almost two to three times larger.

Beyond the short time frame to succeed, publishers depend on the success of platforms to access consumers. Likewise, platforms can't succeed without the presence of highly demanded publishers or game titles. Before carrying on with the behaviors of home console markets it is fundamental to address the publishers operations. The multi-sided nature of the market is key to properly understand the symbiotic dependencies between platforms, publishers, and consumers.

1.4.3 Publisher side.

Game publishers attempt to maximize their sales by estimating the best features on their products design and adopting the best platform to release them. To accomplish this, they have to consider several other publishers' decision making.

TALK Talk about those guys who surveyed networks. TALK Talk about the relevance of networks to evaluate market composition and have an influence map on indirect network effects on consumers.

On the other hand, there are negative direct network effects on other publishers, who are deterred of competing with established firms. In Figure 1.9 we see the composition of publishers and platforms in the fifth generation.

In the Figure, red nodes represent platform firms while green are publishers. Accordingly, the size of each node is relative to the amount of license that firm has. This is also represented in the width of edges connecting nodes. The most successful publishers appear in node array above the others. The graph shows how publishers are divided on those who

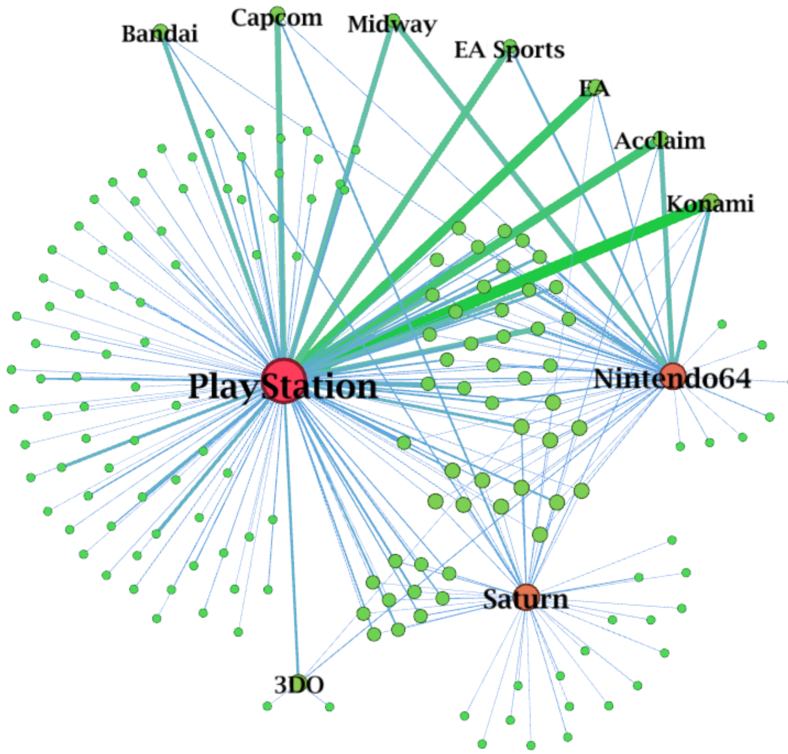

Figure 1.9: Graph of software licences between publishers and consoles (Generation 5).

multi-home and those who do not. Firms that publish to several platforms are significantly larger but still with a relative small market share compared with the big firms (shown on the superior section of the graph with their respective names). Here, we can also appreciate the strong position of PlayStation during this era; being not only the most popular platform among the competition, but also the most targeted platform between the big publisher firms.

As mentioned in the previous section, concentration of the home console market is evident on game unit sales distributions, as seen in Figure **??**. Nevertheless, the extreme volatility of these titles performs under a limited set of publishers, that consequently present a similar market concentration. Figure 1.10 depicts this distribution of publisher firms sales in a logarithmic scale throughout platform generations. Although the industry has clearly grown in the last 10 years, most publishers are just above 100 thousand units while the top

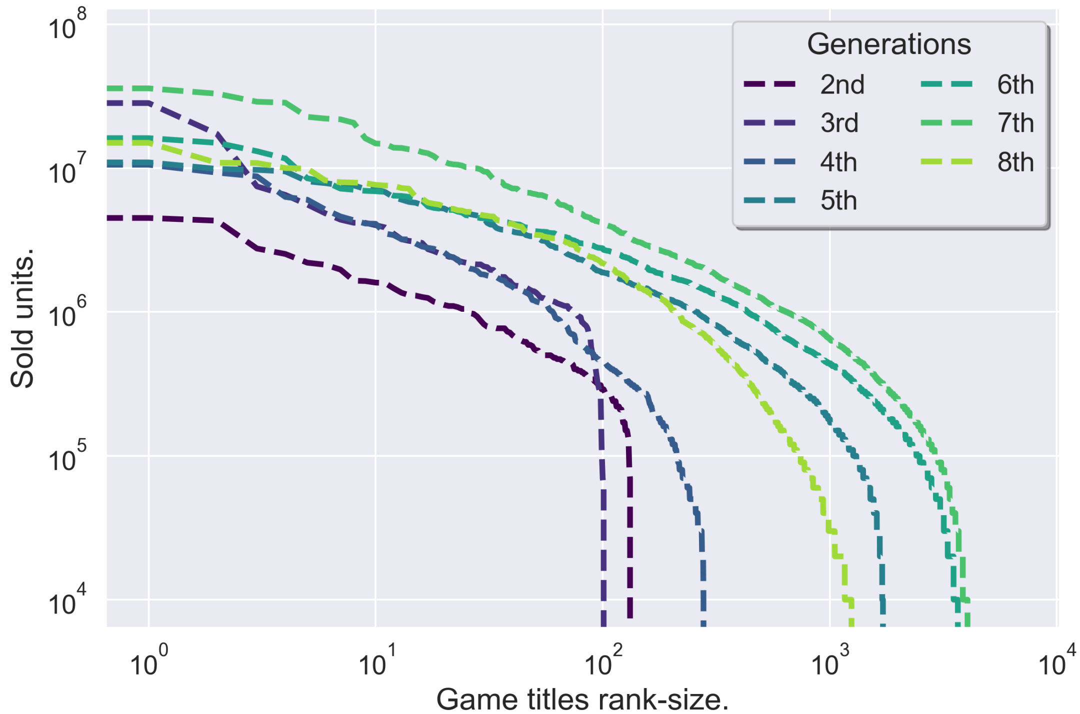

Figure 1.10: Publisher sales distribution by Generation (1980-2010).

25% sells between one and two millions units. Above this, we see firms like Activision or Nintendo with over ten million units.

The market concentration appears to increase through generations. It has also seen issues regarding the amount of games released by publisher presented in Table 1.4. In the Table, it is also possible to see the rise and decline on involved publishers (in the home console). Overall, there are less publishers for home consoles with less releases, but the amount of releases per publisher has increased on average. Most importantly, this smaller population of publishers also has a highly disproportionate amount of releases per publisher. The highest standard deviation among all generations indicates that a few publishers are releasing several times more than others. This is also noticeable in how the 75 percentile releases less than 1.5 units per generation.

Table 1.4: Number of publishers and releases.

Generation	Publishers	Releases	Mean	St.Dev.	25%	75%
III	145	1420	9.79	21.93	1	10
IV	393	2768	7.04	16.18	1	6
V	641	1848	2.88	7.75	1	3
VI	581	5669	1.17	3.28	1	1
VII	269	2012	6.48	40.22	1	1.48

Publisher competition.

The market share of publishers is highly biased towards an exponential distribution. This bias has grown through the years, the third generation shows that starting from percentile 75 firms were publishing 10 or more games. The same percentile in the eighth generation releases barely 2 games. The decrease of mean and increase in standard deviation also indicates this type of concentration in market share as seen graphically in Figure 1.10. This Figure shows how top tier publishers saw an important growth during 2005 and 2010. The reason behind this are mostly multi-homing (having their games in twice or even three times larger audiences) and consolidation of their marketing operations, affiliated developers, and popular franchise copyrights.

The reputation impact of large and established firms is strong in the video game market. They usually control highly valued intellectual property, high quality control, and retain consumer's trust. Firm age may be used as a proxy to differentiate this companies, as older firms correlate with the most successful in the market (with a Pearson correlation coefficient of 0.43). Figure 1.11 illustrates the distribution of sales in logarithmic values and firms age (calculated from first release date).

To properly estimate the relevance of firm's age, we took the total sales per publisher in the last 10 years (with particular emphasis in generation six) and compared it against

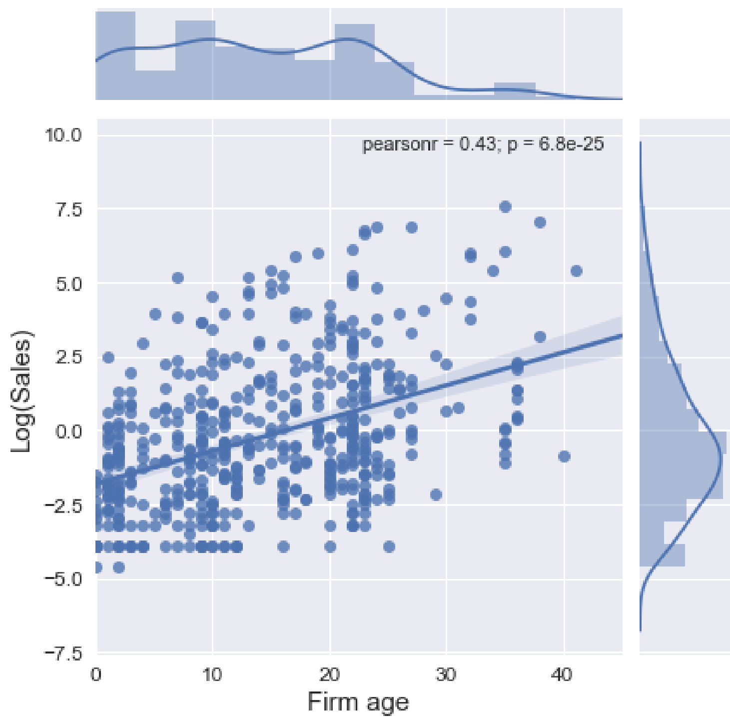

Figure 1.11: Correlation between Sales (Log values) and Firm Age.

firm age, number of releases, and the target platform. Table 1.5 presents the results of the OLS regression to estimate the impact of this variables in total sales. Although the firm age offers some explanation on its games market performance, the selection of the proper platform presents a higher effect on sales variation. Furthermore, it is interesting to note that the Nintendo Wii was the most favorable platform as it was the most widely adopted platform of its generation. This results shed light towards the relevance of platform selection for the publisher side and the historical importance of this evaluation. The econometric approach to detect causality and major effects of parameters like firm age would require additional data to overcome confounding factors. Although this is very limited in pre-internet hardware consoles, additional parameters to address platform issues could be addressed in contemporary physical and digital console markets.

Table 1.5: OLS results of firm age and platform effects on sales.

	(1) Sales (Log)	(2) Sales (Log)	(3) Sales (Log)	(4) Sales (Log)
Firm age	0.155***	0.0799***	0.0469**	0.00621
	(0.0154)	(0.0145)	(0.0170)	(0.0151)
Releases		0.0281***		0.0230***
		(0.00248)		(0.00224)
Xbox 360			1.292***	1.083***
			(0.277)	(0.239)
Wii			1.426***	1.212***
			(0.268)	(0.231)
Ps3			1.301***	0.921***
			(0.276)	(0.240)
Const.	-1.843***	-1.660***	-2.450***	-2.174***
	(0.194)	(0.163)	(0.175)	(0.153)
N	300	300	300	300
R^2	0.255	0.480	0.463	0.604

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Game releases.

The seasonality described in platform sales is also present in the publisher side, as they expect better sales during these months there is an increase on release dates before the high season. On another hand, it is important to consider that the first weekend marks one of the best indicators of any game's success (similarly to the movie industry). Figure 1.12 shows how the concentration of 46% of units are sold on the first week and then heavily decay. This figure also illustrates the great gap between best sellers and unsuccessful titles, seen in the range of first weekend's standard deviation. Under this conditions, publishers attempt to maximize profits by highly promoting before release and selling during the high season months. These pressures on release date and short time span to sell products give seasonality a critical role in the uncertainty of goods' final sales.

1.5 Complement to previous section.

The usual behavior of platform life-cycles follows a common adoption curve. As shown in Figure 1.8, the video market moves in peaks (when platforms achieve market saturation) and valleys (that occur during the transition period between generations). The particular peaks seen in Figure 1.1 also tell the story of how major competitors (namely Atari, Nintendo, Sony, Microsoft, and Sega) had taken the industry for the last 40 years.

Considering the distribution and appearance of only a handful of popularly recognized platforms, the dataset appears to have a high degree of survivorship bias. Data for platforms from generation one and two is almost in-existent in the dataset and elsewhere. Information of consoles and game titles sales is rare, anecdotal, and highly questionable. The same type of bias is present for games and publishers throughout all generations.

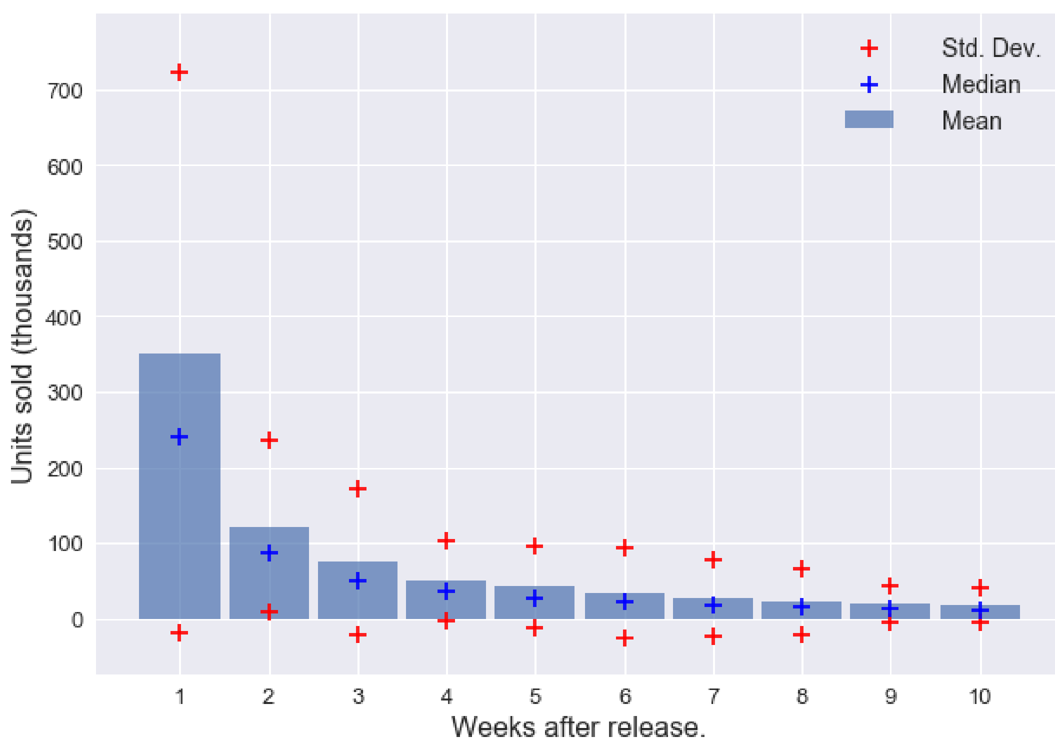

Figure 1.12: Average sales for the first ten weeks.

1.6 Key parameters of the industry's behavior.

To understand the home console industry as a platform market, we should consider the parameters already described and listed in Table 1.6. As discussed, the inclusion of temporal dynamics of the target system is important; as aggregating behavior (e.g. platform cumulative sales) gives little insight into its evolution and effects of other factors. Understanding sides activity through time is key to evaluate the platform's life-cycle stage and the basic state of its organization (e.g. the relative size between sides). Furthermore, if we consider the importance of early stages (i.e. ignition phase) then the representation of time becomes fundamental. Additionally, considering the non-linearity of network effects, we should include the active population of each side (i.e. platform firms, publishers, and consumers).

Table 1.6: Target system parameters and behavior.

	Parameter	Behavior/Property
1	Hardware sales over time	Consumer adoption curve
2	Game licenses over time	Publisher adoption curve
3	Developer-Publisher contracts	Developer firms distribution
4	Platform sales market share	Platform competition
5	Game units sales distribution	Software competition
6	Consumer adoption distribution	Consumer multi-homing
7	Publisher adoption distribution	Publisher multi-homing

Chapter 2: A Model of the Video Game Market.

The history of the video game industry portrays the typical properties of an entertainment or cultural market while operating under a two-sided market model. This combination results in a highly volatile market for producers and platforms that struggle to own a major share in the market or in consumers' minds. The usual blockbuster behavior of entertainment industries is not only an unavoidable regularity, it is also a financial necessity in most cases (as in the tent-pole business model of Hollywood film studios). The following chapter presents a computational model that collects the theoretical framework of multi-sided organizations, economics of uncertainty and information, and mechanisms of social influence. The agent-based model reproduces with different categories and levels of precision the main empirical parameters that describe the process of platform and product adoption, winner-takes-most behavior, and the emergence of blockbusters.

2.1 Agent-based Model.

The model aims to reproduce the main parameters of platform life-cycles by representing the main actors' properties and behavior rules within the disclosed theoretical framework. Thus, the core relationships among platform managers, publishers, and consumers are modeled in a two-sided organization. Meaning that consumers agents evaluate and adopt platforms where they can later purchase game titles. While on the other hand publishers agents will be looking for the best platform prospect to release their software. Platform managers have a less active role in the model on their balance of participation among sides (i.e. licenses and promotion). A single simulation run goes through the life-cycle of the initiated platforms as they naturally grow and decay according to publisher and consumer participation.

The model presented follows the development framework presented by Railsback and

Grimm, among others [Miller and Page, 2007, Gilbert and Troitzsch, 2005, Railsback and Grimm, 2011]. To represent the industrys structure and dynamics Ive developed a rule-based model of home-console production and consumption. The model is an ABM (agent-based model) of console and video game production and consumption that aims to reproduce the main behaviors of the North American industry history. It considers elemental behaviors and decision making related to the adoption of platforms and games. Calibration and external validation of the model was done using data from game and platform unit sales extracted from VGChartz [VGChartz, 2018] and other sources [Nichols, 2014, Herman, 1997]. Model and simulations were done using Python 2.7 and the code is available in the appendix.

2.2 Model overview, design, and details.

Figure 2.1 presents the model's main actors, their properties, and interactions between them in a UML format. The figure shows how the different actors relate to each other and how they make decisions based on their current state and environment. Starting with a single market agent (that serves as the market's environment and keeps records of many simulation experiments), the main three actor objects are created within it. The platform manager object represents the hardware manufacturer or platform firm which interacts with the two main agents and also spawns the console object; which is mostly used to keep track and reference for the remaining actors. The publisher object represents both the publisher and developer operations, being considered as a sole firm as it is in the case of self-publisher independents or big publisher firms with in-house development. This abstraction is done for the purpose of clarity in the model's behavior. Finally, the consumer agent represents both buyers and players at a household level.

2.3 Simulation Overview.

The objective is to represent the behavior of one or more generations of home-consoles platforms and simulate the performance of hardware, game goods, and the collective action of consumers and developers. In the current status of the model, developers make simple decisions to select a platform and develop new software. Platform managers have an even more simple interaction, as they only provide access to the platform and promote participation to developers and consumers. The main focus of the current model is how consumers are influenced by their local social circle and promotion, and how the combination of both finally affects game and platform adoption. Considering the inherent indirect network effects captured in the model, describing and analyzing consumer game adoption also leads to the analysis of the developer counter-part. In other words, a reactive representation of developer's decision making indicates to be sufficient to model the 'blockbuster' emergence while surveying consumers' interinfluences. The agent-based model also allows having several iterations of consoles or generations, meaning that for each platform manager there can

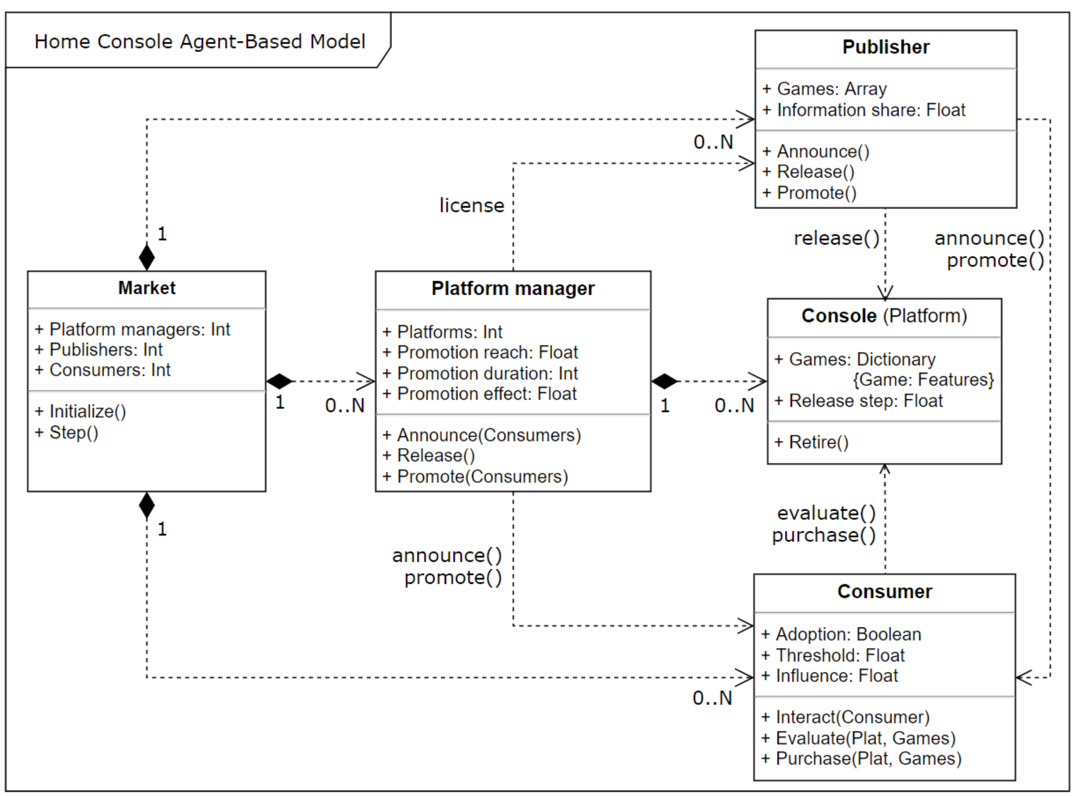

Figure 2.1: Main actors, their properties, and interactions.

be more than one console (where the newest replaces all operations of the previous one).

Consumers agents are modeled at the household level representing the historical trend of one player and one platform per household. This agent considers decision making under product's uncertainty and peer influence through social networks. Consumer also compare platforms on publisher participation and newest release date. This consideration of the other side participation generates indirect network affects on both classes of agents. Publishers decision is also based on partial information on the market, they may only evaluate a sample of total consumers' behavior. Results indicate this set of behavioral rules appears to be sufficient to reproduce the general dynamics of platform competition and 'blockbuster' emergence.

The default simulations consider between 2 and 3 platforms, 250 publishers, and 10000 consumer agents. Consumers are connected in a static social graph by a preferential attachment process forming a scale-free network [Barabsi and Reka, 2002]. The amount of platforms and publishers is exogenously given and does not change. Additionally, firms do not get out of the market when performing poorly, they only remain inactive. Every iteration of the simulation represents one week of the target system. To study the behavior of diffusion, market concentration, and blockbuster emergence throughout the simulations we implement a set of experiments. We analyze the changes in adoption and distribution of market dominance by testing changes in social influence magnitude and market composition. To assess the dynamics of social influence, we perform a sensitivity analysis on the effect of peer-to-peer and mass promotion. For the purpose of this work's simulations, modifications in social influence are based on communication effectiveness rather than reach (in other words, how much it affects the influenced rather than how many it influences). After a benchmark simulation that considers one platform and 300 developers with 10000 consumer agents.

2.4 Design.

The overall dynamic of the simulation goes as follows; first, we initialize with zero adopters and releases for any good. As soon as the simulation begins, consumers share opinions and developers evaluate platform prospects. Agents may adopt platforms before release as the model distinguishes adoption (the decision of purchase) from the actual purchase. Additionally, consumers may adopt only one platform at a time. As soon as a platform agent announces they commence their marketing operations and kick-start the consumers expectations in the market. After 52 simulations steps (representing 52 weeks in the target system) the platform allows access for publishing and purchase. As soon as consumer agents begin purchasing games, the post-experience evaluations shocks the established opinion formation of hardware and software products. Developers release once a platform is available on the market and keep producing immediately after releasing. When they finish a product, developer agents reevaluate the best platform prospect based on the current conditions of adoption and consumer expectations.

As stated before, the model includes only the three main participants in this platform business organization; platform manager, developers, and consumers. Below, a brief summary of each agent's main behaviors:

1. **Platform manager** agents release consoles to the market and manage the platform. They promote their platform to consumers and enable access to developers.

2. **Publishers** adopt a platform and release compatible games. They maximize their expected utility based on the consumer side adoption and developer presence among platforms.

3. **Consumers** are represented at the household level. They face two decisions; adopting a platform and then adopting particular games for that platform. Consumer agents have to speculate based on their past experiences, social influence, and partial information.

Table 2.1 presents the main agents' properties and their values. The market agent is implemented as an environment class that enables other agents interactions and keeps information of the simulation states. Initialization values presented in this table belong to the baseline calibrated simulation. General results on the model output are based on this initialization. This simulation considers 350 iterations or steps to represent the average lifespan of historical generations (i.e. around 6 years of operation). Accordingly, platform manager agents only release one device per simulation. All goods, hardware and software, are modeled as a vector of size 10 which components are random values under a uniform distribution. Consumer preferences is modeled in the same manner, making the effect of both preferences and product features irrelevant for the purpose of this study. This

Table 2.1: Model and simulation parameters.

Agent	Parameters	Values	Value range	Initialization
Market	Consumers	Integer	[2000,200000]	10000
	Publishers	Integer	[50,500]	250
	Platforms	Integer	[1,4[	3
Consumer	Social influence	Float	[0.0,1.0]	0.2
	Adoption thresh	Float	[0.0,1.0]	0.6
	Search reserve	Integer	[0,[	0
	Expectations	Float	[-1.0,1.0]	0
	Preferences	Array	[-1.0,1.0]	Uniform random
	Wealth	Float	[0.0,1.0]	Uniform random
	Adoption	Boolean	Boolean	False
	Purchase	Boolean	Boolean	False
	Playing	Boolean	Boolean	False
Publisher	Bound	Float	[0.0,1.0]	0.1
	Develop time	Integer	[0,[	52
	Production	Integer	[1,3]	1
	Units sold	Integer	[0,[	0
Platform	Promotion reach	Float	[0.0,1.0]	0.7
	Promotion effect	Float	[0.0,1.0]	0.01
	Promotion period	Integer	[52,104[	52
	License limit	Integer	[0,[	1
	Releases	Integer	[0,[	1
	Release step	Integer	[0,[	55

modeling decision is purposefully intended to ignore the role of quality in an experience market, having each purchase follow the main characteristic of experience goods.

The generality of the simulation process goes as follows; first, it initializes with zero adopters and releases for any given good. As soon as the simulation begins, consumers share their expectation values and publishers evaluate platform prospects. When a platform agent announces they commence their marketing operations and kick-start the expectations of consumers, which indirectly affects publisher's evaluations. After 52 simulations steps, the platform is released allowing access for publishing and purchase. Consumers' post-experience evaluations begin affecting the opinion formation of hardware and software products. Publishers may produce only if a platform is available on the market. As consumers and publishers begin adopting platforms, indirect network effects contribute to platform's snowball effect and the an uneven market emergence. Performance of platforms also affects software sales, which also shapes market concentration on the publisher side.

2.5 Details.

2.5.1 Consumer agent.

The consumer class represents the consumer population at the household level with the assumption of one active gamer per household, which until 2018 was the empirical regularity [ESA, 2018]. The population is connected by social networks where a node represents the sole consumer in a household and edges represent social ties. The purchase decision of this representative individual reflects those of the household. The mechanism of influence that ultimately develops each agent expectation and decisions is based on an opinion dynamics model similar to a voting model. This mechanism generates most of the non-linear behavior and complexity of the model and thus its behavior was surveyed by its own at first. Before addressing the details of other agents, we will be describe and present the preliminary results of the social influence sub-model.

Social influence and product evaluation model.

To model the consumer behavior on the platform market, we first modeled the behavior of social interaction, expectation adjustment, purchase decision, and product evaluation. The following sub sections refer to the modeling of consumer behavior regarding its interaction with its first degree connections and the available products.

A. Products.

The model of peer influence and purchase decisions considers the presence of a product space $\mathcal{P}$ of ambiguously defined goods (i.e. cultural or experience goods). Within it, there are P number of products with Q number of features (Equation 2.1). All products have the same amount of features and each feature value is a real number within the continuous range of $[-1, 1]$. A product description $\vec{c}(p)$ is based on its Q features, as described in Equation (2.2).

$$\mathcal{P} = \{p_1, p_2, \ldots, p_P\}, \qquad P = |\mathcal{P}| \tag{2.1}$$

$$\vec{c}(p) = \{c_1(p), c_2(p), \ldots, c_Q(p)\} \qquad where \quad c_j(p) \in [-1, 1] \tag{2.2}$$

The vector of the product features $\vec{c}$ is defined to have L_2 norm $||\vec{c}|| = 1$[1] and are only available to consumers after purchase.

The use of a vector representation allows a simple but scalable model of any multi-dimensional product. For the purpose of the agent-based model, the product space $\mathcal{P}$ represents all the games available for the consumer (i.e. those that have been released and their platform is still in the market).

B. Consumers.

For the influence model, the consumer population $\mathcal{A}$ considers a total of A individuals which state is composed by four properties. The state of an individual a is represented

[1] L_2 norm is $||\vec{c}|| = \sqrt{\sum_i c_i^2}$

by: *a) satisfaction expectations* represented by a vector $\vec{\epsilon}(a,p)$ with one element for each product; *b) feature preference* is a vector $\vec{\pi}(a)$ of dimension Q representing preference for each corresponding product feature; *c) ownerships* $\vec{\beta}(a)$ is a vector of size P which elements are $\beta_i(a_j) = 1$ if a_j owns p_i and 0 otherwise; and finally a vector Γ that contains the network neighbors of the any individual a_i.

$$\mathcal{A} = \{a_1, a_2, \ldots, a_A\}, \qquad A = |\mathcal{A}|$$

$$where \quad State(a_i) = (\epsilon, \pi, \beta, \Gamma) \quad \forall a_i \in \mathcal{A} \tag{2.3}$$

Thus, for each product p_i there is an expectation value $\epsilon(a, p_i)$ in the agents' indexes. Expectation value is a continuous number within $[-1, 1]$ and is represented as:

$$\vec{\epsilon}(a,p) = \{\epsilon(a,p_1), \epsilon(a,p_2), \ldots, \epsilon(a,p_S)\} \ where \ \epsilon(a,p_i) \in [-1,1] \tag{2.4}$$

The ownership index $\vec{\beta}$ simply represents the products that agents have purchased and experienced.

$$\vec{\beta}(a) = \{\beta_1(a), \beta_2(a), \ldots, \beta_S(a)\} \tag{2.5}$$

$$\beta_i(a) = \begin{cases} 1, & \text{if a owns } p. \\ 0, & \text{otherwise.} \end{cases} ; \qquad 1 \leq i \leq S \tag{2.6}$$

Preferences values π are continuous and uniformly distributed between -1 and 1. As with vector $\vec{c}$, the preferences vector is defined to have a norm $||\vec{\pi}|| = 1$.

$$\vec{\pi}(a) = \{\pi_1(a), \pi_2(a), \ldots, \pi_Q(a)\} \qquad \forall p \in P; \quad \pi_i(a) \in [-1,1] \tag{2.7}$$

Finally, we consider the social ties that are included for the calculation of the new expectation value. This network is based in a number of connections Γ that consider the set of individuals that are connected with the agent where $\Gamma(a) \subset A$.

C. Consumer rules.

The particular behavior of the consumer agent will depend on the ownership status of the products. If a consumer agent a_i is not an owner of a product p_j, it will update its expectations according to the information given by its neighbors as detailed below. On the other hand, if the agent becomes an owner it evaluates the product; fixing the outcome of this evaluation to the product's respective expectation $\epsilon(a_i, p_j)$ value. After that, the agent does not change this expectation but other agents are able to request this value through their own pre-experience evaluations. The decision for ownership is based in an arbitrary exogenous given threshold T explained below.

C.1 Pre-purchase expectation update.

Expectations and ownership are the only parameters that change over time in the model. The evolution process of agent's expectations (i.e. $\epsilon(a, p)$) considers the expectations of all other individuals within it's network $\Gamma(a)$. Thus, $\epsilon_t(a, p)$ depends on other agents expectations in $t-1$ (Equation 2.8). As the agent asks all neighbors for all product features we say that its expectations are composed as in Equation (2.9), where $|\Gamma(a)|$ is the number of connections in $\Gamma(a)$.

$$\epsilon_t(a, p_j) = F(\epsilon_{t-1}(b, p_j), b \in \Gamma(a)) \tag{2.8}$$

$$\epsilon_t(a, p_i) = \frac{\epsilon_{t-1}(a, p_i) + \frac{\sum_{b \in \Gamma(a)} \epsilon_{t-1}(b, p_i)}{|\Gamma(a)|}}{2} \tag{2.9}$$

C.2 Purchase decision.

Once the value of $\epsilon(a,p)$ is above the threshold value of T, the agent a purchases product p and the corresponding $\beta_p(a)$ value is set to one. Agents can't disown the product, once a certain β value changes it can't go back to zero and the respective expectation will also stay at the resulting value of the utility evaluation.

$$\beta_p(a) = \begin{cases} 1, & \text{if } \epsilon(a,p) > T \ ; \ T \in [-1,1] \\ 0, & \text{otherwise.} \end{cases} \tag{2.10}$$

C.3 Post-purchase utility evaluation.

When a product is purchased, the agent evaluates the utility that the products features give by contrasting them with his own corresponding preferences. The result of the evaluation is the utility value $U(a,p)$ given by a dot product between $\vec{\pi}(a)$ and $\vec{c}(p_i)$, as presented in Equation (2.11). As vectors $\vec{\pi}(a)$ and $\vec{c}(p_i)$ are normalized, this assures that always $\| \pi(a) \| \| c(p_i) \| = 1$, then we say that the dot product is equal to the vector's angle cosine (Equation 2.12. Thus, for the purpose of evaluation, the utility of any product is also equal to the outcome value (Equation 2.13).

$$\vec{\pi}(a) \bullet \vec{c}(p_i) = \| \pi(a) \| \| c(p_i) \| \cos\theta \tag{2.11}$$

$$\cos\theta = \vec{\pi}(a) \bullet \vec{c}(p_i) \tag{2.12}$$

$$U(a,p) = \vec{\pi}(a) \bullet \vec{c}(p) = \cos\theta \tag{2.13}$$

Considering that the vector $\vec{c}(p)$ is known, the exact position of $\vec{\pi}(a)$ is not known for each value of $\cos\theta$ that is not -1 or 1. This range of the preference vector's solutions is a cone with a given angle of θ. Vector similarity could also be used as an evaluation method for neighbors' hidden preferences. As agents may recognize the limits of a cone range around the product features, they may also speculate and evaluate distances between their preference cone and their neighbors. Let's consider individual a_i which neighbors always acquire and experience all products before him. Neighbor a_j already experienced p_i and it's utility value $U(a_j)(p_i)$ is known for the individual a_i.

As a representation of consumers' experience, the evaluation of a product reveals its features' values $\vec{c}(p_i)$ but it's not possible to say that preferences $\pi(\vec{a})$ are evident to the individual[2]. Regardless of the agent's awareness, the contrast between the features and personal preferences produce a significant and noticeable response and we consider this outcome to be the individual's utility $U(a,p)$. The evaluation of utility considers the distance between the preference and product feature vectors in a Q dimensional space. The angular distance between them indicates their similarity and to calculate this similarity a simple dot product is needed considering that the vectors are normalized and their respective norms are equals to 1. Thus, for the purpose of product evaluation we say that utility is represented as,

$$U(a,p) = \vec{\pi}(a) \bullet \vec{c}(p) = \cos\theta \tag{2.14}$$

As the range of $\cos\theta$ is a real number between -1 and 1, we say that features and preferences are in absolute disagreement when $U(a,p) = -1$ and absolute agreement if this value is 1. These properties satisfy the conditions of individual attitudes being numbers in this continuous range.

[2]As awareness of feature preferences may be conscious or sub-conscious.

Figure 2.2: End state of a sub-model simulation in a circular topology.

D. Model simulation.

The described model was implemented as an agent based model. Vectors $\mathcal{A}$ and $\mathcal{P}$ represent a collection of objects with the described properties $State(a_i) = (\epsilon(a_i), \pi(a_i), \beta(a_i), \Gamma(a_i))$ as previously discussed. After initializing all agents with their respective uniformly random values, the simulation proceeds following the mentioned agent's rules. Each step of the simulation all agents evaluate pre-experience expectations for all products unless they already have purchased and evaluated it. In figure 2.2 we see the final state of the simulation with a circular network topology and only one product available. Each unit in the horizontal axis represents an agent and the vertical axis indicates utility (either expected or final). Red bars show the utility of agents that decided to purchase, blue ones reflect its expected value. As expected, neighbour expectation or utility values affect individuals. In the case of purchase, utility may be affecting the values of closer agents.

Additional behavior rules and parameters.

In addition to the mentioned model of influence, consumer agents have other properties and behaviors. As the model considers multiple goods the behavior of purchase is somewhat different. Expectations are modified as specified in the influence model for each of these products. When there is a decision to buy a platform based on the adoption threshold, the consumer agent will become an active adopter and immediately adopts the game with the better expectation. Consumer agents will start playing the game each simulation step if the utility evaluation results in a positive outcome. Additionally, to represent playing activity and interest decay all agents engage with a specific title only for a limited amount of steps. After that, they will look for another game available in the market that has the highest expectation.

Consumer's expectation do not depend only on neighbors expectations, as developer and platform firms are able to promote their products affecting the expectation value on a subset of the consumer population. The promotion effect (i.e. how much it alters the expectation for the specific product) is set to 0.01 for all simulations. The preliminary analysis and experiments presented below were executed with slight alterations of promotion reach, or how many consumers are randomly selected to be influenced by the promotion effect. Finally, the consumer agent activation scheme runs through a simple sample of the 50% of the population each simulation step.

2.5.2 Platform manager agent.

The platform class represents firms that incur in the platform business model by providing hardware device and management of developer licenses. Platform managers have an intermediary role between publishers and consumers as both agents have to adopt the same platform for their basic interaction. The default class of the platform manager limits games releases to one per publisher, without any limitations for entry on the consumer side (which is also limited to only one platform for the base model simulation). Consumer participation growth presents positive marginal returns unlike publishers, who are more sensitive to the platform network effects. Limitation of exclusive licenses to enhance their sales or to ensure basic quality in their products are both reasons to monitor the participation of publishers. As quality is based in random distribution in the model, the platform class accepts any attempt of publishers to release a product. The number of releases and the simulation step of release for each console is given exogenously as an input of the model (see table 1.6), each release represents the major console for a single life-cycle or generation. Before any release, manufacturers announce and promote the future platform to the consumer side. In reaction to this, publishers immediately begin surveying for adoption rates among consumers and the decisions of other publishers. The effect of platform promotion kick starts consumer expectation and its diffusion through the social network, which may finally trigger adoption decisions if there is sufficient positive expectation. From the simulation step of platform release the games produced by publishers will be available for compatible consumers. The default class of manufacturers has a reactive behavior and it does not impose any additional incentive on either side.

The platform promotion affects consumers expectations by slightly modifying the expectations of a sample of consumers. This modification is based on the 'promotion effect' value while the size of the consumer sample is given by the 'promotion reach' parameter. The promotion procedure occurs every step after the platform announcement until the steps given by 'promotion period'. Every consumer agent selected modifies its expectation of the respective platform by adding the 'promotion effect' value. The baseline value of 0.01 would represent an 0.5% increase in the expectation value range of consumers (i.e. from -1, to 1).

Publishers.

This agent class represent established publisher and self-published developer firms. Although there is evidence of publisher licenses concentration in real market, the model considers an equal state where all firms work with one license at a time with no multi-homing.

Beyond initial equal market power, games software quality also has an equal effect by having its features modeled with a uniform random distribution. As consumers preferences are represented the same way, the evaluation of product features has a random distribution. Using the peer-influence sub-model we selected a size 10 for product features $\vec{c}(p)$ and consumer preferences $\vec{pi}(a)$ vectors. This decision was made based on convenience of representing the final utility in a Gaussian distribution, as this type of distribution is the outcome of the sub-model when we use vectors with size 10.

As the platform agents announces a new device, the publisher class will attempt to find the best prospect. The publisher agent evaluates each platform by participation of competitors, the amount of purchases, and consumers' expectation. As depicted in equation 2.15, the publisher gets an estimated value of $\tau(a)$ for each platform a. The agent goes through a sub-set of the consumer population C and calculates the average of its purchase states $\vec{\beta_i}$ and expectation values ϵ_i. A platform's value would be this average over the total presence of other publishers in the platform $\delta(a)$.

$$\tau(a) = \frac{\frac{\sum_i^C \vec{\beta_i}(a) + \vec{\epsilon_i}(a)}{C}}{\delta(a) + 1} \tag{2.15}$$

After selecting a platform, the publishers begin development and promotion. Different from platform firms, publishers have a fixed 'promotion reach' of 0.01 (one percent of the population) and a 'promotion effect' of 0.01. Following the market typical trend of heavily promoting new games before release, the promotion behavior ceases after release step. Additionally, once the game is released this agent class will re-evaluate the best platform prospect, without any influence of their previous adoption decision. The class iterates over this process until the simulation ends or there are no active platforms.

2.6 Other details.

Simulation initialization values depend on specific scenarios to be tested. Most relevant parameters to consider are the market share of existent platforms and multi-homing costs; consumers' attitude formation, adoptions, and experience values; and developers' platform adoption. For calibration and validation purposes, we executed several simulations with one, two, and three competing platforms. Each simulation was repeated for one and two releases per manufacturer. Simulation steps or ticks (i.e. a complete iteration of the market's activation) represent one week of the real market operations.

The sensitivity analysis presented in the results section were performed for scenarios with one, two, and three competing platforms. For each scenario we increased the peer-to-peer influence by one decimal from 0.1 to 1. Correspondingly, we did the same with mass promotion, altering influence by five units from 5 to 20 percent of consumer audience.

2.7 Sensitivity Analysis.

To properly analyze the behavior of the model it is important to clarify the behavior of one platform without competition. A parameter sweep was performed on peer-to-peer influence and promotion reach. Social influence was increased by one decimal from 0.1 to 1. Correspondingly, the same was done with firm's promotion, altering their reach in the same manner. Given the low output variance between simulations, each combination was executed only 15 times. Averages of these simulations outputs were then compared with empirical data. Table 2.2 displays the outcomes between the lower half range for social influence and the upper range of promotion reach, indicating their coefficient of determination.

The sensitivity analysis shows how the rate of adoption and market share behave compared to empirical surveys. The comparison of typical adoption curves of platforms is depicted in table 2.2. Gross similarity appears to be more sensible to changes in social influence rather than promotion. Although promotion reach affects the size of adoption it

Table 2.2: Coefficients of determination (R^2) of simulations with one platform.

Parameter	Social Influence	Promotion reach 0.4	0.7	1.0
Consumer Adoption	0.1	0.9842	0.9877	0.9762
	0.2	0.9909	0.9887	0.9923
	0.3	0.9932	0.9895	0.9909
	0.4	0.9840	0.9831	0.9823
Publisher Sales	0.1	-0.3186	-0.2217	-0.5478
	0.2	0.6858	0.6504	0.6944
	0.3	0.7275	0.7537	0.7279
	0.4	0.8297	0.8341	0.8254
Weekly Sales	0.1	0.4194	0.3640	0.4034
	0.2	0.3782	0.4128	0.3892
	0.3	0.3708	0.3655	0.3983
	0.4	0.4267	0.3752	0.3711

doesn't affect the total distribution of the simulation output. As a single platform simulation does not compare platform market share or releases per platform, table 2.2 only displays the effects of social influence in consumer adoption, publisher sales, and weekly sales. Consumer adoption appears to be highly similar throughout most parameters, with a slight maximum on 0.3. Similarly, the weekly sales fit doesn't with promotion reach nor social influence. Although the coefficient of determination is low for games' first ten weeks, the qualitative similarity of its behavior marks a significant resemblance (specially if we consider the variance of standard deviations). On the other hand, publisher sales distribution appears to be highly sensitive to social influence. As individuals expectations are more affected by their influential peers, the distribution of publisher total sales changes from an almost linear distribution towards an exponential shape.

Results in this figure show the diffusion curve with only one platform in the market. It is important to note that variation in the curve convexity and inflection points is a key aspect to understand how diffusion is formed. Usually, a steeper beginning reflects higher external effects like mass promotion or relative low costs of adoption. On the other hand, the first inflection point may portray the influence of social influence.

The variations on the sensitivity analysis indicate that at the highest values for promotion and peer influence, the diffusion curve becomes unnaturally fast. The values to calibrate the model to empirical data also depends on the amount of platforms in the market. should be below 20% consumer targets and 100% local influence. Figure 4 also shows how the other extremes fit irregularly close to the target. The diffusion curve of the higher values shows the non-linear relationship between local and mass influence.

2.8 Results.

Simulation results reproduce several aspects of the phenomena described about the home console market. Parameters like consumer adoption, publisher adoption, and publisher sales have a significant quantitative similarity, while outputs concerning weekly sales, platform market share, and relative share of releases have a qualitative similarity. Although the output fitness varies according to the number of platforms simulated, values do not change in a significant manner. Results reveal the formation of high market concentration in the publisher side is positively related to the amount of information that spreads through consumers networks and how influential are their relationships. The shape of average and median consumer adoption curves are strongly susceptible to promotion. As presented in the previous section, the simulation outputs of adoption generally have a significant fit with the typical diffusion within a generation. Across all simulations, weekly sales results do not have an accurate representation of the surveyed data. On the other hand, it does represent the usual behavior in a qualitative manner.

Figure 2.3 present the average outputs for the target parameters of the model with two platforms. As this is the minimum configuration that implies multi-sided competition, it may be used as a benchmark to understand the behavior of agents and compare results with simulation including more than two consoles. Given the described simulation parameters and initialization, results portray a smaller scale of the target system. Thus, to present a comparison between the data and simulation results values have been normalized by feature scaling. All the outputs presented in the figure consider the initialization parameters as

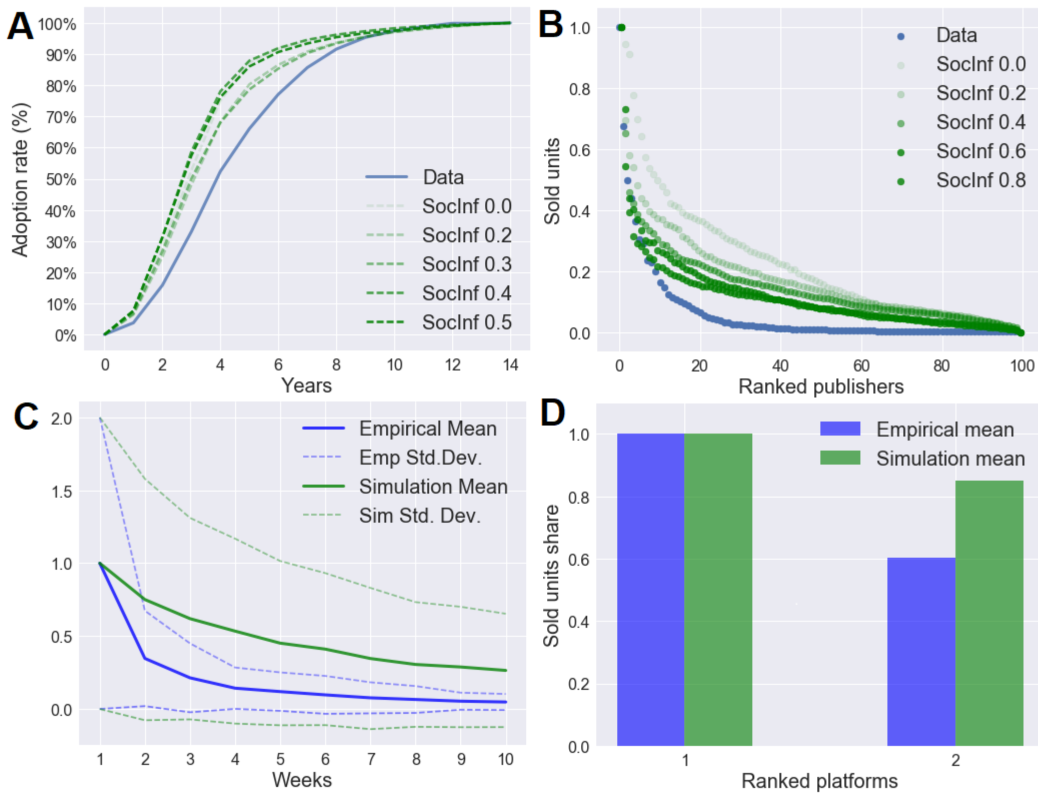

Figure 2.3: Average simulation outputs for Two Platforms (Normalized).

stated in the previous section with promotion reach set at 80%. On the upper left of figure 2.3 (A) we have the average adoption rates for the lower rates of social influence compared with the empirical data. It is possible to appreciate that on higher levels of influence the adoption becomes faster. Additionally, higher effects of peers shapes publisher sales (B) towards the typical distribution in the target system. On the lower left quadrant of the figure (C) the broad similarity of weekly sales displayed. Similarly, platform market shares are reproduced in general terms.

The general results of the presented simulations show how the concentration of markets with ambiguous products may be explained by peer influence and, additionally, be affected by the multi-sided organization and massive promotion. Even with uniformly distributed features of firms and products, the sole effects of this mechanisms is significantly shapes the volatility towards some preferred products and their producers (i.e. blockbusters, 'rock-star' firms). Regarding the production and reception of these cultural and experience goods, the model generally reproduces the extreme uncertainty and market concentration. Although results present an approximation to the target in system that is quantitative and in part qualitative, the implementation of the model presents a concrete alternative to explain how decision under complete uncertainty shapes the modeled entertainment platform market.

2.8.1 Consumer adoption.

The simulation outputs present a significant similarity on consumer adoption curves. Most importantly, it clearly reflects the inflection points usually attributed to internal effects of diffusion [Bass, 1969]. Accordingly, external factors also appears to be highly determinant to adoption. Thus, both promotion and peer influence affect the shape of consumer adoption. On simulations with a range of 40% to 80% of marketing reach, the model behaves according to empirical evidence with a slightly faster rate after the mid stage. In these cases, peer influence appears to be positively correlated with increased mid phase adoption, while the firms' massive influence affect the initial phase of adoption. Presence of promotion usually accelerates adoption and overcomes the effect of peers. Simulations with strong promotion show how the sigmoid shape of the curve tends to disappear, favoring lineal increments on early stages.

The number of competing platforms also affects the output of consumer adoption. Figure 2.4 displays a comparison on the effect of platform population based on simulation outputs with 20% of social influence and 80% of promotion reach. The effect is clear on simulations with four consoles, where the initial contribution of internal effects seems negligible. These results are mostly affected by the addition of more expectation changes given by the platform firms, as there are more of them the amount of expectation modification grows and affects consumer adoption. To address this issue, future work should consider including an adaptive sensitivity to promotion like a proportional increment of tolerance to promotion.

It is important to note that when the release date of platforms is too close (i.e. less than four simulation ticks), the representation of typical adoption behavior is highly biased by the 'loser' platforms. The platform with the earliest entry gains the advantage and the following consoles underperform, which later affects the average and median measures of the adoption curves. The historical data of platform adoption and sales is subject to a high degree of survivorship bias; platforms that enter the market and barely make an impact aren't properly registered. Results of simulation with closely competing platforms could possibly be reflecting this irregularity.

2.8.2 Publisher sales.

Adoption behavior on the publisher side appears to be highly sensitive to consumer adoption. As consumer agents begin to reveal a collective preference, publisher agents swiftly adopt and generate a lock-in for other consumers and publishers. Nevertheless, this behavior is similar to the target system, where publishers are rapidly concentrated on one platform. The model limitation of only one license per publisher at the same time prohibits the typical adoption of multiple platforms, which also affects the proper evaluation of the model performance regarding publisher adoption. If we consider that multi-homing is

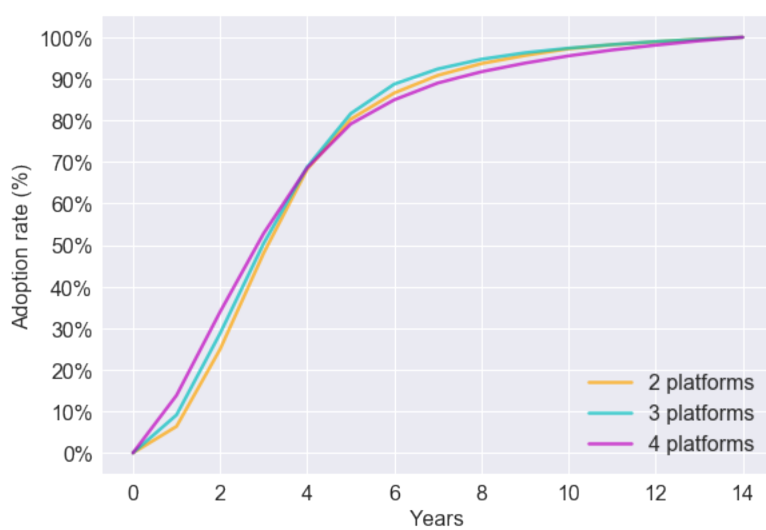

Figure 2.4: Adoption shape by platform numbers (Normalized).

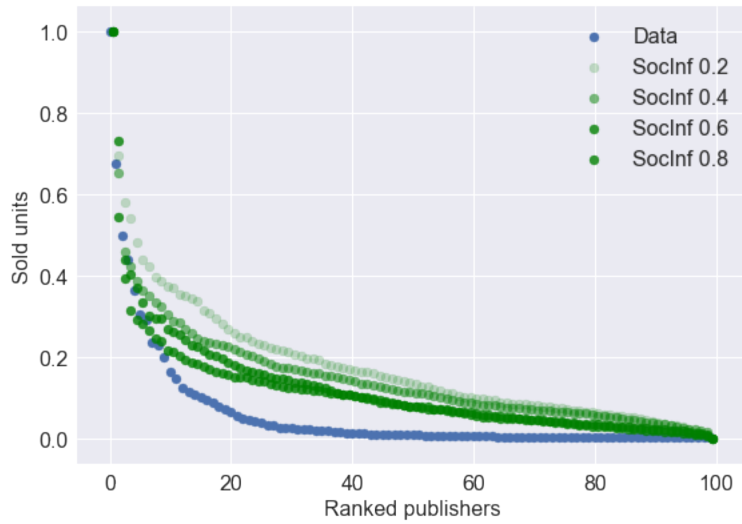

Figure 2.5: Game units sold by Publisher (Normalized).

mostly based on multiple releases of the same game title, then the first release leads toward the platform of choice. According to this, behavior of publisher agents does qualitatively reproduce the target system. Regarding publishers sales, the amount of platforms also has an important effect on its distribution shape. This effect is mostly given the constraints on internal two-sided markets for publishers. Thus, the market concentration appears bounded by the leading platform. Even more relevant to publisher sales distribution is the effect of peer influence, which is positively related with higher market concentration. Figure 2.5 presents the distribution of publishers for the empirical evidence and the simulation output for several degrees of social influence. A higher effect on peers expectation change shapes the units sold by publishers from a linear distribution towards the exponential order seen in the data.

The difference among publishers' market share increases with peer influence. As peers have a higher impact in expectation changes, the shape of unit sales ranking is affected. It is important to note that regardless of the social effect, the dynamics of consumer agents naturally produce a biased distribution with partial information and uncertainty naturally produce. Overall, it is clear that higher promotion may create noise and instability in the information flow and platforms performance. Peer's information becomes more relevant when there is more information in the market.

2.8.3 Game sales after release.

As shown in figure 2.3, the output of weekly sales does not comply with an accurate proportion of sales during the first weeks. The games market usually presents a large proportion of sales to happen on the first weekend. Although the model does not capture this, the distribution of sales through time is not uniform. Simulation outputs present a natural decay on game title sales through the weeks.

2.8.4 Platform market share.

Similarly, the amount of console units sold by platform reflect a general similarity. The average market share of platforms on any given generation (shown in figure 2.6) do present a linear decay but with a marked difference between the two leader platforms. The figure below presents the average final ranking with five platform agents. This result may be explained by the relative short duration of 'domination' during the simulations. Although platforms remain active for long periods they only achieve to engage in high indirect network effects and block the competition for a short time. Thus, it opens the possibility of a second platform to gain more sales.

Simulation results show how the model in platform market share seem to be closely related to the first-mover advantage. Particularly given that the first platform to announce gets the first batch of developers. Regardless of mass or local influence, the earliest platform gains market dominance in the short-term. The initial advantage of any platform generates a larger market share difference when peer influence is high. Although this influence may help insurgents to rise, it appears to be consistently in favor of the incumbents (which would be expected of platform competition). As previously stated, the model does not differentiate between firms and all platform agents promote with the same magnitudes. Inclusion of this type of power asymmetry could be used to better assess the effects of promotion in this

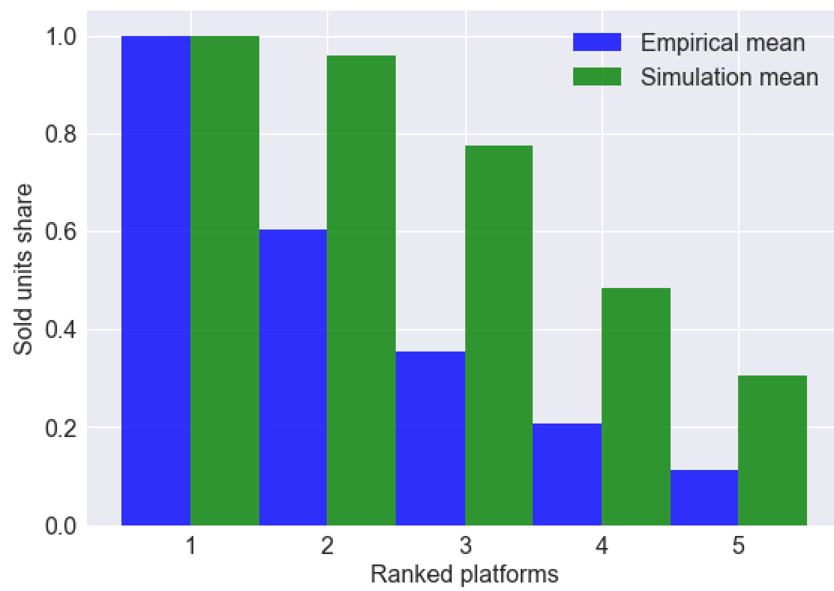

Figure 2.6: Market share of five platforms (Normalized).

parameter.

2.9 Conclusion.

The entertainment industry has historically been subject to high market concentration and extreme uncertainty. While some firms usually seize the market, they are permanently prone to failure on any new product release. With the disruption of platform organizations, entertainment adapted its business model making the industry even more sensible to concentration and volatility. Economic and sociological theories suggest that this is shaped by uncertainty and social organization. The implementation and calibration of the presented agent-based model is an example of how uncertainty influences the home console game industry. The particular effects of social influence and platform competition are addressed and explored using rule-based simulations. Results indicate that social influence is critical for the formation of market concentration on publisher firms. Initial explorations on the effect of marketing and social influence indicate that there is a complex interaction between mass media and local information. While mass media tends to create initial impressions, these are modified by social interaction. A higher spread of promotion may neglect the effect of peers. Platforms market share seem to be robustly in favour of one firm being the dominant in the short-term but replication of the 'winner-takes-most' does not occur on the long-term. On the other hand, local interaction seems to be fundamental for the uneven performance of games goods. The adoption of some platforms and games results as a massive shock, similar to what we see in the industry's history. Although further analysis of the diffusion of information should be done, we can conclude that peer-to-peer and mass media influence co-exist in a complex manner, promotion accelerate diffusion while peer information contributes to the discrimination between products. Depending on a platform's reputation, properly adjusting the efforts of word of mouth or mass media marketing can be critical. As expected, knowing which mechanism to address may help reverse or ameliorate negative public opinion.

The agent-based model is presented as a decision making support tool and offers the possibility to be extended.. Future research should include: multi-homing, publishers asymmetry on promotion, consumer memory of publishers, consumer ability to detect product features, among others. Particular emphasis should be put on platform strategy regarding price structure and the management of incentives. Additionally, it is important to consider that products were modeled uniformly and firms do not specialize. Although the presented approach may be adequate for experience or cultural goods, given their ambiguous features, it is less appropriate for platforms market in general. The presented results on the diffusion of platforms shows a significant first entry advantage, which is usually true in competing platforms within the same category; but platform's strategy usually aims to high differentiation. The model responds to the similarity in home console (e.g. Xbox versus PlayStation) or others markets like film and series streaming platforms (e.g. Netflix versus Hulu). To properly address platform behavior this similarity should not be generalized or considered the norm. Usually, platforms differentiate to access unique demands on their target audiences; like the coexistence of Twitter and Facebook.

The presented model reproduces the typical behavior of the home console market in North America in the last 30 years. To do this, the behavior and organization of actors was fundamentally driven by social, economic, and behavioral theory. Current developments in entertainment platform markets present the advantage of large datasets with significant detail. A proper analysis of data on products features and actors behavior could greatly benefit this model and, by the systematic analysis of its behavior, further understand the formation of blockbusters and entertainments' high market concentration.

Chapter 3: Extensions to the base model.

3.1 Introduction.

So far, this dissertation has presented the history, theoretical framework, and stylized facts regarding the general behavior of the industry. After that, based on the empirical findings and a theoretical background, we proposed a computational model of high uncertainty products within platform markets. Given the methodological nature of agent-based modeling, their use in simulation should favor its ability to explain rather than to predict or to accurately describe with detail the behavior of the target system. This is why the third chapter of this dissertation focuses on the applications of the proposed model towards understanding the complex behavior of this market while providing a framework to assist strategists and managers in their understanding of the system and decision making.

Among the many reasons to use an agent-based model of the video game industry, we can highlight several benefits to the analysis of entertainment markets or content platforms. First, the model contributes to the representation and survey of non-aggregated dynamics of products' diffusion. Considering the relevance of diffusion dynamics in today's complex and agitated markets, it is key to recognize that adoption doesn't happen at a synchronized time, a centralized location, or even with perfect information. The many levels of behavior that compose a diffusion process go from structural aspects like economic constraints, culture, and individuals' social network, to other subtleties like adopters similarities, mechanisms of information transmission, or external events. Thus, the diffusion of any innovation is a complex process that requires an analysis of its underlying forces. With the use of agent-based modeling, we can test the effects and behaviors of what we know about such forces. As in the Bass model [Bass, 1969], we can see that aggregation is important and that the adoption process may be justifiably generalized to characterize the system's behavior. But, to get into the underlying behaviors, theory and models are very limited and generalization can only be possible if available data permits a proper analysis. The use of an ABM pretends to contribute using theoretical models calibrated with empirical data. Thus, it does not mean that it fully explains the target system, it rather surveys the behavior of the model based on what we know of it. Secondly, the agent-based methodology contributes to represent and survey the non-linear growth of multi-sided organizations. A model of platform strategy and economics could benefit its study and understanding. In the same degree as the study of diffusion, platforms depend on similar underlying factors that may explain the state of the system and provide insight towards the next steps. An agent-based approach helps to represent not only the diversity of actors and its behavior through time, it facilitates tracing the behavior of specific individuals or groups. Although this traceability is very restricted to simple models [Aizenbud-Reshef et al., 2006], it could benefit these areas and, as in this case, contribute to survey the effects of cultural or experience products on the market. Both the platform and cultural economy are simple yet complex enough systems to address our current knowledge with this type of methodology.

Beyond the interest of developing agent-based models to better understand these markets, the model extensions presented in this chapter allow to address specific questions from the relevance of information availability to strategic decisions on platform management. We present a set of modifications to the model presented in chapter 2, where the purpose of implementing these new attributes, rules, and conditions, is to provide more insight on the already established motivations, questions, and objectives of this dissertation. Furthermore, it serves as an example of the use of ABMs as a decision making support tool. More specifically, the objective of these extensions is to a) present the relative effects of additional parameters and behaviors on the market dynamics; and to b) demonstrate the value of agent-based model as a decision support tool in a complex and highly unpredictable social system.

3.1.1 Extensions to the model.

As already mentioned, the model is extended within three major aspects: the implications of quality in an uncertain market, the effects of consumer information, and platform management. Each of these aspects included a modification the base model along a sensitivity analysis explorations before running the experiments. The most important elements that were modified in each of these extensions are:

1. **Group product features and consumer preferences.** The first extension includes the delimitation of consumer and feature categories; having several types of properties allocation for both type of agents instead of randomly given. This exploration surveys the notion of quality and its relevance within the model's definition. It allows to explore the impact of properties heterogeneity and how its effects on building hype. Following with the base model, the subjective quality of the products is represented by a dot-product of two same-sized vectors. Consumers have an n sized set of preferences that are modeled as attitudinal values between -1 and 1 [Ross et al., 2011]. As in the base model, products are modeled as experience goods; meaning that consumer agents cannot evaluate products features [Nelson, 1970]. The general simulations in this section test how different types of consumers and products affect the simulated average expectation, adoption rates, and the competition of the software side and hardware firms. As products features and consumer preferences can now be previously defined with detail, this enables the experimentation on the effect of specific combinations of consumer and product segments. Following the work on diffusion [Rogers, 2003, Valente, 1995] we put attention to heterogeneity of diffusion going beyond typical consumer and innovation properties. The inclusion of diverse properties permits the study of different underlying diffusion paths that generate similar behaviors at the macro level.

   Additionally, the inclusion of product types is also extended to the firm's production properties. So far, the features that satisfy consumers' preferences where based in random distribution without marking major differences between them. The first extension takes care of this issue allowing to set specific values and creating segments. Another way to understand quality is through the firms capacity to generate the desired features. This extension considers that features are a direct consequence of the developers attributes. On another hand, it also provides the definition of product features for platforms, allowing the conjoint evaluation of platform and game products.

2. **Consumer perception.** The base model included a relatively significant role to consumers' social psychology and basic decision making under uncertainty. Although it is not of our interest to expand into complex cognitive capabilities, we do think it is necessary to consider memory and product evaluation for the purpose of studying the weight of experience goods in this type of markets. Remembering firms that provided a desirable result would be important signal for posteriors decisions, as it typically is in entertainment and experience goods markets. On the other hand, complete unawareness of the product features falls easily into an extremist position. In reality, consumers are not absolutely blinded to the product they decide to purchase. Beyond recommendations and reviews there is also a personal evaluation based on some elements that characterize the product (e.g. movie genres or the artistic style of an avant-garde director). The extension in this section mostly focuses on the inclusion of a limited evaluation of product features before purchase. Once again, the purpose of these modifications is to understand how they affect the macro behaviors of market concentration and diffusion.

3. **Platform strategy.** A final section goes through the definition of several extensions and basic experiments regarding platform management. The first set of experiments covers a survey on the effect of time of entry within the model. A second section goes through the implementation of multi-homing behavior for consumers and developers. A series of experiments go through the changes in macro-level behaviors based on the activation of either both types of multi-homing by their own and simultaneously. Finally, a prototype of platform access costs is developed to test the effects of price

structure.

The extensions presented above contribute to demonstrate the relevance of computational modelling to address issues like marketing segmentation, product design, consumer information management, and hypothetical scenarios for platform ignition and sustainability. They also allow to consider multiple theories of the market's behavior in an interdisciplinary framework. Beyond academic theories, this type of model permits the inclusion of any observable or hypothesized behavior (being a stylized facts, particular data collected for a specific market and condition, or a practitioner's mental model). For example, the model may put to test the idea that the market is driven by product quality against other possibilities (i.e. being driven by brand recognition, blockbuster installed base effect, or the network's topology influence).

Each following section reviews the purpose, description and additional configurations of the model, and experiment results of the extensions described above. Before a detailed review on each, a preliminary sensitivity analysis is presented to benchmark the behavior of the model with the new rules, parameter values, and initialization settings. Section 2 surveys the behavior changes related to consumer preferences and product features value distributions. Next, section 3 goes through the inclusion of consumer evaluation; or in other words, the effects of decreased uncertainty in the model. Section 4 refers to aspects of platform management with experiment simulations on platform release dates, consumer and publisher multi-homing, and comparison of entry costs and incentives. Finally, conclusive remarks and a discussion of the practical and theoretical implications is presented.

3.2 Extension 1: Product quality and consumer preferences.

So far, the representation of heterogeneity on products and consumer's preferences is given by random values in a uniform distribution, which represents a market with products inherent with complete uncertainty for the market's actors. The simulations presented in chapter 2 used vectors of size 10 to represent these properties. In both cases, the first two values of the vector were fixed to 1 on the consumer case and a positive real number between 0 and 1 for product features. This modification was included to avoid an extreme situation of uncertainty and to test scenarios where adoption of products and platform was favorable. These fixed values represent the minimal certainty that consumers have over the product they purchase, or the commonly known elemental aspects of the product's format (i.e. the experience of going to the movies, reading a book, or eating at a restaurant). This extension presents specific fixed sets of values for consumers and products, which aim to represent a market with groups or categories of consumer and product types. The simulation's purpose is to explore the effects of similarity among consumers or products on the macro behavior of the market. Using the simulations, the model contributes to understand how different combinations of these consumer and product types may alter platform and/or product adoption rates, market concentration, and ultimately the formation of blockbusters. Market research attempts to simplify the behavior and nature of consumers to acquire actionable insights for the business operations [**?**]. The basic notion behind this reduction is to operate with defined segments where consumers are supposed to share similar conditions (i.e. age, disposable income, gender, or preferences), which facilitates decision making and ensures a return of investment. This extension does not include the definitions of age, income groups, or any other concrete quality. The numerical representation of these segments allows to set different types of consumers based on these preference values. Thus, the model does not imply or consider any time of relationship between other characteristics and preferences (i.e. values are independent from each other). Based on the researcher's approach and particular consumer model, the categorization of these values may be considered to be dependent of other biologic, socioeconomic, or cultural traits.

The differentiation between consumers allows to have groups of consumers that partially share some preference between each other. Say for example, having two types of consumers with a vector size of 3; group A has a preference of [1,1,0,0] and group B one of [0,1,0,1]. Agents of group A and B share half of their preferences (the two in the middle). Products which features that strongly match the shared preferences would become highly regarded

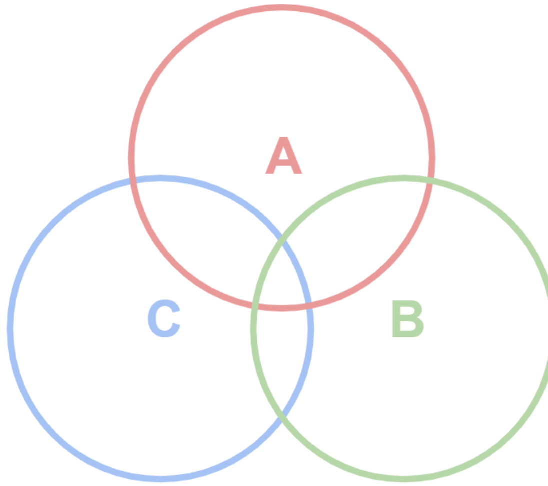

Figure 3.1: Venn Diagram of Consumer Segmentation.

and adopted (e.g. [0,1,0,1]). A product that only caters one consumer group may have a good response (at least from the segment with a better fit), but it is also likely that it has a negative response depending on the diffusion process (as consumers that do not have a good fit may dis-encourage others to adopt). As represented in the diagram of 3.1, the multiple combinations of consumers may provide several intersections. These intersections become target of market segmentation and product design, as they increase the likelihood of a positive response.

The vector representation of agents properties can be used to define the differences and similarities for both products and consumers in the model. The given distributions used in this chapter are hypothetical scenarios for the purpose of exploration and demonstration. Nevertheless, further empirical surveys could strongly contribute to defining the product and consumer properties distributions, particularly the preference patterns of consumer agents related to other properties like income, geographical location, or needs. As this extension permits the exogenous definition of products and consumer attributes distributions, both are modified to represent categories, cliques, or subgroups. Questions like how product similarity affects market concentration or how adoption rate is influenced by consumer's homophily may be addressed using this framework. Thus, the first extension adds the model's understanding of similar groups effect on the market behavior while providing tools to define situations where consumer segmentation is important.

Simulations of Extension 1.

The simulation experiments presented in this section survey the possibilities given by preference distributions and answers specific questions about the video game industry model. Depending on the particular simulation, we include two, three, or more platforms to the experiments. The usual simulation output is based on the average or typical behavior of 20 runs per initialization. Beyond explicitly mentioned changes to the simulation and initialization values, the parameters and rules settings are based on those defined in the base model (chapter 2).

The modifications of this section are based on defining a priory the particular distributions of preference values among n sets of consumers with the same preference. Following the simple example of consumer segments in the previous section, let us consider a hypothetical market with half of the population having preference values with a value of -1 and the other half with the opposite value of 1. This polarized scenario allows to test how random products, product categories, or individual products (with unique properties) would interact with consumers and consequently generate different adoption patterns. Likewise, we can assess how these interactions affect producer firms and indirectly influence platform firms. Continuing with the simple example, absolute categories of good and bad products (i.e. 1 and -1 respectively) can be included for the model's analysis of success rate regarding affinity between product features on one side and consumers' preference and influence networks on the other. This section follows with a systematic survey of macro-behavioral changes based on consumer preference and product features groups. First, we present a preliminary analysis on the consumer preference and product similarity. Which, before assessing how multiple types of preferences modify behaviors, allows to evaluate the role of fixed identical preference values over random ones (which have been used by them model so far). After presenting the results on consumer preferences and product features, we go over results of experiments with basic segmentation. A second part reviews the impact of platforms as a product, surveying the effects on adoption and game sales. Finally, we present the analysis of different segments under the presence of products that fit one type of consumer (which we reference as 'ideal' or targeted products).

3.2.1 Preliminary exploration on agent properties similarity.

Before the simulation and analysis of properties categories, we proceed with a sensitivity analysis of the main parameters to modify consumer preference and product features. The main purpose is to assess that the model behaves under the expected range and to distinguish new behaviors from the original settings. Results serve as a point of comparison or benchmark of the typical behavior, which permits a proper analysis of the posterior experiments. Thus, the behavior of the next several experiments can be compared against the original model and the changes seen on this sensitivity analysis. For this preliminary sensitivity analysis we gradually modified the vector component values of consumers and products. The modification consists in modifying an additional component value from a random uniform value to one for every different simulation. Starting from a vector with its first two components with a value of one (where all other values are given by a random uniform distribution), each subsequent simulation would modify the following component to 1 as well. After 8 iterations (given that the vectors' size is 10), the vector values are all set to one. Similarly, we do this incremental modification for product features while keeping consumers preference set to the original form. For each case we describe noticeable results and insights.

Preference sensitivity analysis.

After the analysis we can conclude that at higher similarity of preferences between consumer agents, there is a higher impact of social influence. A higher similarity of preferences makes peer information more effective for all agents. As consumer agents become more similar, the utility values of others is equivalent to any single agent. Thus, as the simulation develops, the collective awareness of products is provided through the experience of all agents; having the population be almost certain of which products will have positive returns by later steps of the simulation. Interestingly, this situation fits with one of the premises of seeking information on the behavior of others. The principle of similarity among peers as discussed in the seminal paper of McPherson et al. defends that individuals already incur in homophilic relationships [McPherson et al., 2001], which would also explain our intuitive trust on peers for decisions under uncertainty. The simulation results also shows how peer similarity contribute to this situation. We see how different preferences would occasionally generate bad advice when peers have already made an evaluation of products. In this case, as our agents trust other agents in the market regardless of their attributes, evaluations become worse as they are based on other individuals' preferences. The effect is evident if we take a look on the development of expectations through different levels of preference similarity and platform competition. On simulations with one platform, expectations grow gradually positive for similarities below 70-80% with a peak of 0.1818 average positive expectation. Close to

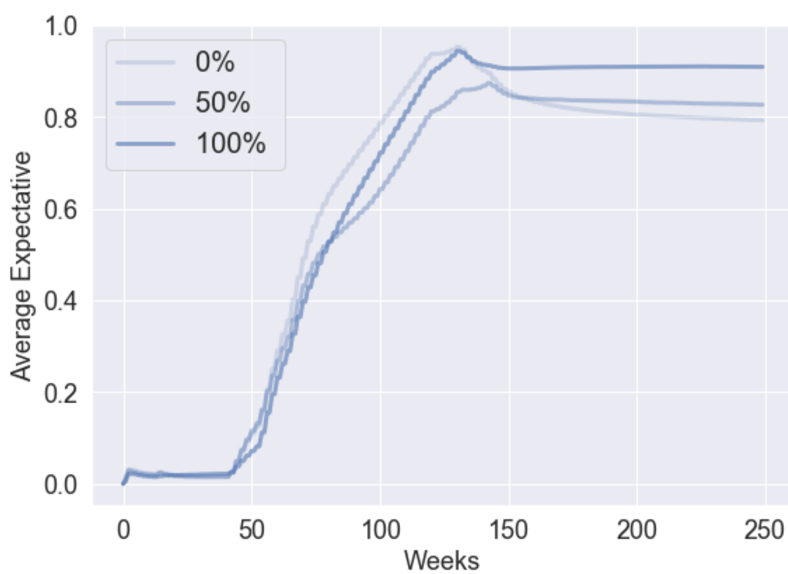

Figure 3.2: Average expectation changes on Preference S.A. with Two Platforms.

an absolute similarity the growth of average expectations becomes almost twice as faster starting from the platform release week, and closing towards the end of the simulation with a peak of 0.3677 in positive expectation. When we analyze expectations for two and three platforms we see how expectations grow quickly and then settle after consumers evaluate the available product. A higher preference similarity generates a significant boost in platform participation. For the case of two platforms, expectations increase at first and around 140 weeks they've decrease from their peak and begin stabilizing. As seen in Figure 3.2, when similarity is near 0% or 100% between consumers, expectation grows strongly into an average peak of 0.95. Although complete diversity shows a rapid growth in expectation, it also suffers the largest decline when product evaluations and social recommendations settle. On the other hand, mixed diversity achieves a lower peak at a slower speed, but it typically stabilizes near its highest value. From this behavior, we could state two conclusions for a market of high uncertainty and high consumer similarity would be that: a) consumers attitudes find a stability, and b) expectations growth is significantly affected by peers diversity. When the market has three platforms, the threshold to acquire critical mass appears to be assisted by additional promotion activity and new content development up-time. Another interesting finding is that partial preference heterogeneity ends with better expectations than experiments with absolute diversity. We suppose that the faster growth backfires as more people become interested but ultimately disappointed. This is an important lesson about promoting a product, if the objective is to promote faster adoption rates then it is critical to assure that the appropriate consumer segment is engaging and there are no relevant peer effects to different consumer segments.

The effect of preference similarity is also evident in platform adoption. On experiments with one platform, only some runs show platform ignition. Additionally, among those that do make it, the adoption rate is slower and more likely to be formed by social influence. Simulations with two platforms show the best fit for empirical trends among these experiments, particularly for median adoption rates where all levels of similarity adjust to empirical evidence. On three platforms the situation remains similar for lower levels of similarity. As with expectations, adoption appears to be boosted by the promotion of more platforms and the continued supply of new games. When preferences are majorly similar in this market composition, adoption rate is abnormally fast and with a steep initial growth (as it is the case with strong external or mass promotion influence). Thus, the behavior is more likely to be explained by consumer agents basing their decision on expectations formed by previous announcements and releases. As we can see below, for simulations with two and three consoles there is an important surge in adopters on the second platform to release. Figure 3.3 shows respectively the average adoptions rate in two and three platform markets. In the case of A, the second platform achieves the highest adoption regardless of similarity. Still, full preference heterogeneity has less participation overall compared with other levels of similarity. Furthermore, we see that at higher preference similarity there is a linear uptake on adoption. For three consoles on the market (P1, P2, and P3), represented on the right panel, we see that the second and third platform generally do better than the first. And the third platform to release usually takes the consumers among the decaying second. Different from the second to release, the latter firms have similar participation levels. The effect we see in panel A appear as if the second and third consoles 'piggy-ride' the expectations generated on their processors, allowing it to excel in the case of complete trustful information. Compared to Panel B, it is evident that the third platform (P3) does

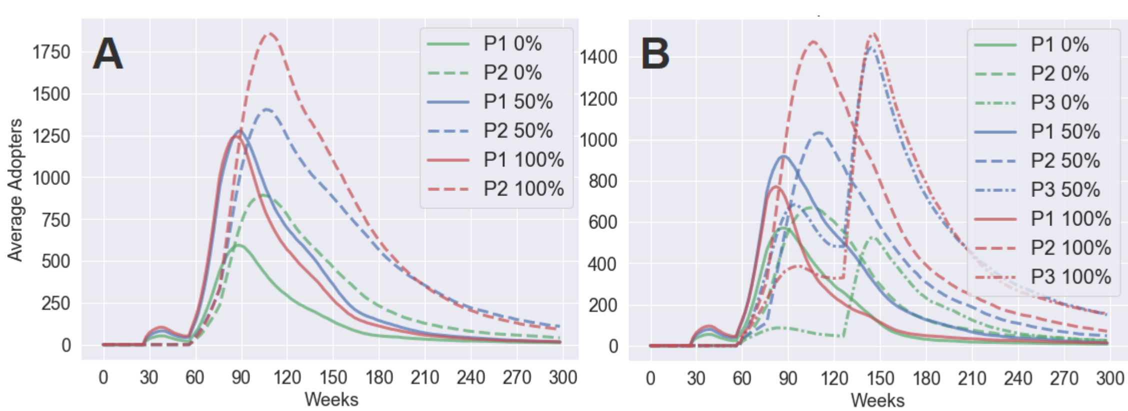

Figure 3.3: Adopters on two (A) and three (B) platforms.

outperform the second one (P2) on average; but the gap between them is not as large as in panel A or their own comparative distance with P1. This is probably because of the competition that the additional platform brings to the table, as P2 retains consumers, P3 basically shares what the second platform in panel A would only gain by itself. These behaviors raise the question of how far from each other should platform releases if they are competing for the same category (given that the current simulation does not consider platform differentiation).

Overall, we see that preference similarities have an important effect. This effect becomes more evident when similarity is larger. As discussed, this distribution becomes virtually a zero uncertainty landscape, at least in terms of the mechanism of social influence and the accuracy of its information. Although products remain uncertain and unpredictable,information from neighbors that have already tried it becomes a perfect tool to evaluate for all consumer agents. Thus, we see the expected effect on positive feedback between agents on expectations first and adoptions later.

Features sensitivity analysis.

For the analysis on the effect of feature similarity results show that the presence of higher similarity has a negative impact on adoption and expectation formation. Additionally, concentration for platform and publisher firms appear to be worse when there is higher similarity of products. As features are fixed and equally likely for any product, they don't seem to have any effect on the market when there is only one platform. Adoption doesn't significantly change and neither does publisher concentration. Even in this configuration, adoption curves fit the empirical sinusoidal shape of console hardware sales. On another hand, expectations values do have a significant change related to product similarity. On the lower bound (i.e. as products attributes become uniformly random), the average expectation and adoption usually stay below compared to those simulations with higher similarity. This suggests that higher product heterogeneity does not contribute to a better expectation growth in a market with product uncertainty. The effect of higher heterogeneity is also

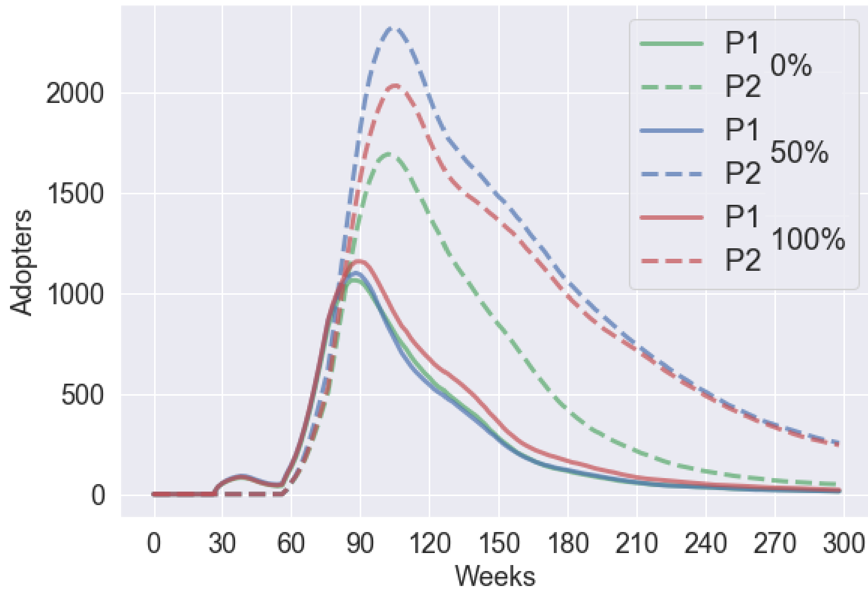

Figure 3.4: Adopters for different feature similarity with 2 platforms.

present when there are two platforms in the market, a case that better represents the effect of higher product heterogeneity in expectation and adoption. Although platforms from simulations which products do not have similarities under-perform compared with higher similarity, those that are completely similar also have less participation. 3.4) displays the similar behavior on the first platform, and the marked effect of product diversity in the second one.

Another remarkable fact about runs with two platforms is the difference on market concentration among them. With no similarity, the market is shared by almost a 0.5 share each while publishers have an HHI index of 0.00652. When similarity rises, platforms share changes abruptly to 0.823 in favor of the second platform. For publishers the concentration also changes against them to an HHI index that goes to 0.019 when all products are identical. Figure 3.5 presents a single simulation output that reflects this behavior. On Panel A, the two platforms that are able to coexist are those with 0% of similarity. Interestingly enough, it is the second platform to release that gains traction faster but followed closely by the first one. For higher similarities the behavior changes towards one 'winning' platform, the

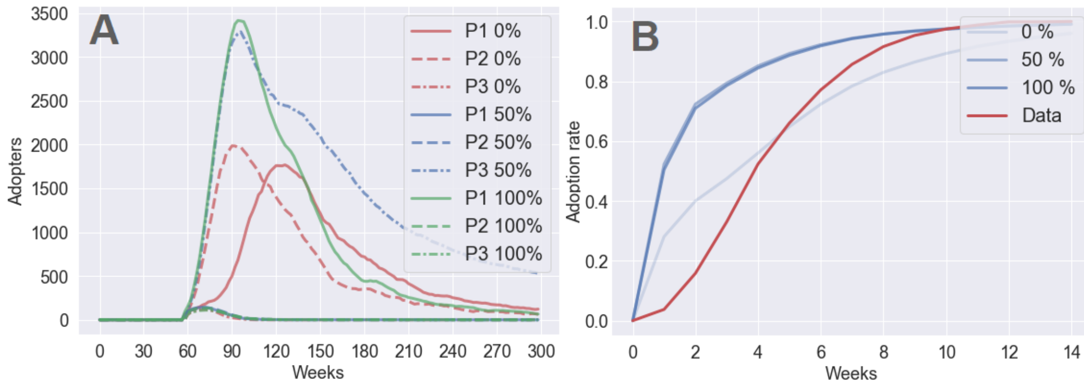

Figure 3.5: Adopters and adoption rate by feature similarity with 3 platforms.

third platform for 50% and the first for 100%. Paying attention to the average expectations growth, we can say that these simulations strongly suggests that additional promotion accelerates positive expectations and consequently the adoption. This acceleration is evident if in the adoption rates for each run (Figure 3.5 B). For this market composition, higher similarity and promotion activity contributes towards a faster adoption with a reduced influence of the 'first-come' advantage. The issue presented by the model is the heavy promotion acceleration evident in Panel B, which is accentuated with higher similarity. Thus, it appears that three platforms do provide an impact with higher promotion levels, but it is with low product similarity that this evolves into ignition of more than one platform firm. When similarity is greater, then the extra 'hype' goes towards one of the available consoles, following the winner-takes-most formula. Expectation also follows the same growth rates as adoption as it would be expected, having 0% similarity a slower but positive and consistent development.

General remarks for segmentation and product features exploration.

During the presented preliminary analysis of preference changes, we've seen that the effect of being similar provides an indirect trustworthiness to other agents' information (which would be the natural motivation for vicarious evaluation and the assumption of homophily). The effect of this higher similarity generates a 'piggy-ride' effect between subsequent platforms, which perceive adopters in gradually larger batches. Results for this preliminary survey also show that there is a significant impact of product features over platform adoption and the system's behavior. When game's features are different and have no common features, platform adoption doesn't follow a critical mass to attract as many consumers. In turn, if products are similar adoption tends to be on a single platform, with increasing speed relative to the amount of platforms. With these results regarding feature and preferences discrete changes, we now proceed to evaluate particular conditions over these parameters as it is usual and expected to see in real target systems. The following scenarios consider hypothetical segmentation of consumers and product diversity availability. The results of this extension are presented in three groups. Each of these groups on segmentation will be presented by scenarios with one, two, and three platforms of market composition. The first group considers simulations regarding two types of consumers, the simulated market typical behavior, and the hypothetical scenarios of an 'ideal product' to analyze the difference between product features (i.e. random, all the same, mixed, or ideal for a specific set of preferences). The second group addresses 'ideal platforms', where platform attributes are taken into consideration. And finally, a third group goes through a mix of platform, product, and multiple consumer types at once.

3.2.2 Extension 1.1: Basic segmentation.

We now study the behavior of the market if there is a minimum of two different type of consumers. The first experiment surveys the effect of product similarity with two different classes of consumers. The amount of groups of significantly similar attributes which in this case are two groups of consumer preferences. One of the benefits of agent-based modeling is the inclusion of any additional dimensions of parameters, which makes modeling and reproduction of heterogeneity a challenge. In this experiment, we shift from completely heterogeneous consumer preferences to groups or segments that share an identical configuration of preference. This precise definition of consumer attributes allows to test the model assumptions and behavior based on two or more type of consumers. For the purpose of this experiment, half of the consumer agents will be given values as described in 3.1. Half of the agent population has a *typeA* set of preferences while the other half has a complete opposite of *typeB*. The influence network is randomly generated without relation to these properties, meaning that for the purposes of this experiments the model assumes no homophily. On another hand, the product values on these simulations go from an array of random uniform values, up to a ten-sized vector of ones. This last configuration favours both types mentioned with at least half of their preferences. Additionally, some simulations use an 'ideal' value for product features, making them exactly like any type of consumer preference.

$$\begin{aligned} typeA &= [1, 1, 1, 1, 1, -1, -1, -1, -1, -1] \\ typeB &= [-1, -1, -1, -1, -1, 1, 1, 1, 1, 1] \end{aligned} \tag{3.1}$$

To survey a general framework to study segmentation using the agent-based model, we defined some simulations for this group. For different levels of product similarity we executed two simulations: 1) two types of consumers as depicted in 3.1, 2) two type of consumers but half with a vector of positive ones and the other half with negatives ones. Additionally, two other simulations where done using an 'ideal product' for consumer type A (i.e. with the same vector values), forming: 3) two consumers as 3.1 with all products designed for type A, and 4) two consumers with preference as in simulation 2 along the type A product. First, let's go through the behavior of the distribution mentioned in 3.1.

Two types of consumer agents.

Results for simulations with one platform and two type of consumers (along several values of product similarity) reflect that the product similarity is not relevant for platform formation and publisher sales distribution. This does not hold true for other market compositions, but as there is only one platform the behavior is relatively stable regardless of product's

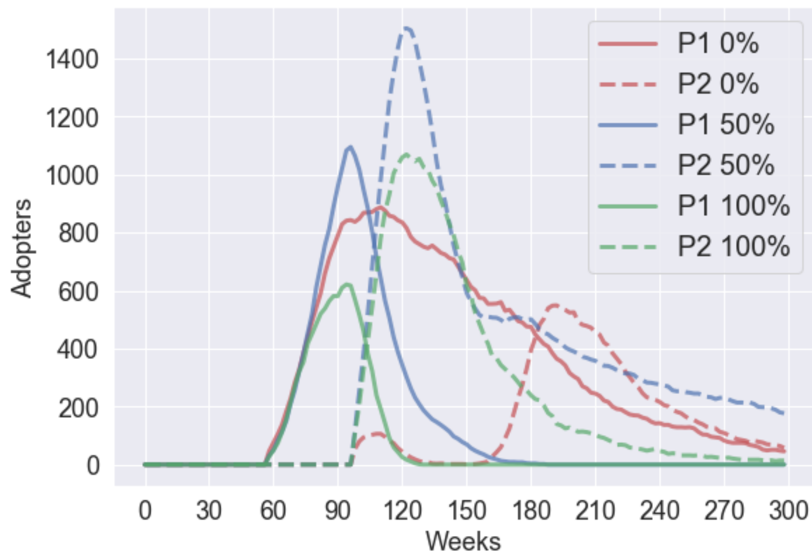

Figure 3.6: Platform adoption over different product's features.

composition. On each case the platform seems to ignite amassing adopters up to 14% of the total population, making it larger on average than other simulations. Average and median adoption rates fit with empirical data while the publishers distribution follows a qualitative similarity but with a thick long tail. We compare this basic scenario to the other simulations where the type A game product is in the market. In this case, adoption is even higher with almost 25% of potential consumers. Everything else does not appear to be significantly different from the general simulation of two consumer types.

Simulation results for this experiment reveal that when 0% of product features share similarities there is a severely slower adoption curve, with a loss in the characteristic sinusoidal shape. Figure 3.6 compares the platform adoption of the mentioned settings, revealing this underwhelming adoption rate that we already discovered in the preliminary sensitivity analysis of features. The major difference between fully heterogeneous and the two types of preferences can be seen in the speed of platform adoption and the convexity of the sinusoidal curve of adoption.

When the simulation runs with three platforms, results show a defined behavior pattern. Regardless of product similarity, one of the platforms significantly overpasses the others. The HerfindahlHirschman index for the three platforms stays over 0.9 for all levels of similarity. Interestingly, there is a typical decline on the total amount of adopters when similarity is at the extremes. Making a mix of similarity and diversity apparently contributes to a higher adoption on the consumer side. On the developers' side, the effects seem to be none; with similar patterns of adoption and distribution of market shares. Now, if we compare the same situation but in a market where half the population is clearly benefited by the available products, while the other half dislikes it. Imagine we model the adoption of a product that you either like or you don't. We know how the consumer agents behave according to products' diversity, with this simulation we now survey the extreme effect of having one type of consumer benefited at cost of satisfying the other type. The differences between these two simulation (i.e. two type of consumer with and without ideal products) rise mainly in publisher sales.

When the products cater one type of consumer more than the other, the distribution of game sales favour a limited amount of publishers. This behavior is reflected on an abrupt decline on sales. We see this behavior in all simulations with an ideal product and in some market compositions when similarity was set at 100%. In Figure 3.7 we may appreciate how the rank-size of firms is related to the size of this sales 'plateau'. The figure presents a single simulation output as this plateau disappears when we aggregate all simulations (i.e. average sales rank). When only one platform is in the market the distribution keeps a continuous decline, but when we include more firms we see how the tail gets chopped in some of the simulations. As the HHI is an aggregated figure, it does not reflect this type of distribution increasing from a 0.0065 with one platform to only 0.0118 with three. The interesting fact about these chopped distributions is that usually, in terms of the model's behavior, a larger platform adoption (as we see in these simulations) means that almost all developers dedicate their releases there, shaping the typical distribution.

Thus, this means that when we necessarily have a product that satisfies part of our population, the amount of platforms may affect how positive information flows through the consumer side; impacting the speed of information diffusion. As we have more promotion information and a separation of some developers to other firms, there is an important advantage to some firms. If the outcome of their relatively boosted games is positive, then it creates a positive feedback where it is very likely that consumers purchase another game if the positive expectation remains within clusters of the influence network. For the purpose of this simulation exercise, we can conclude that the amount of firms may contribute to higher publisher concentration under these precepts.

To address how the particular values affected the model instead of the actual difference among preference sets, we tested with other compositions like full vectors of one and a counterpart with negative ones. Results from these simulations do not present any quantitative nor qualitative significant difference.

So far, the extension surveyed how market concentration may have unexpected reactions when there at least two distinctive types of consumers. The presence of platforms opens paths for consumers and developers that ultimately shape the market's distribution. A

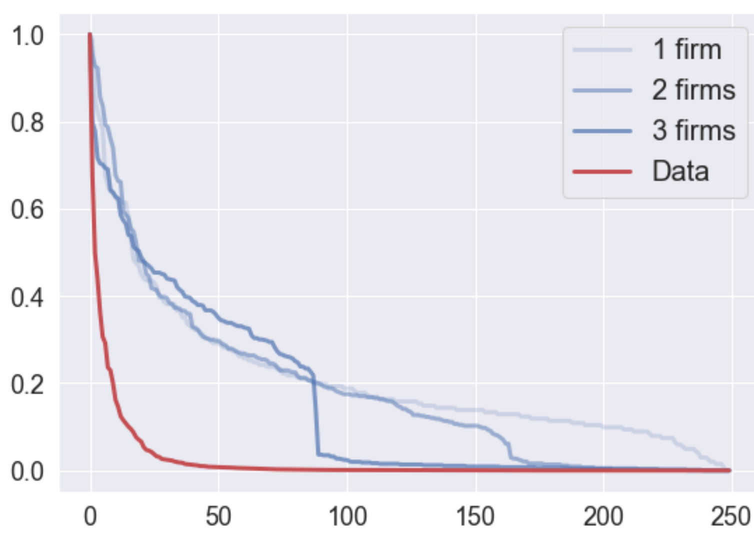

Figure 3.7: Publisher sales rank with different market size.

critical part of this process, is the actual response to the platform as a service or product. To include this factor on our hypothetical scenarios of the platform behavior, we present the results when they are given features that consumers directly evaluate. After this, we proceed to include targeted products along with additional scenarios of consumer types.

3.2.3 Extension 1.2: Platform features.

To properly asses the complex and symbiotic behavior of game and platform adoption, it is important to consider the platform properties relative to other competitors. Establishing the features of platforms allows to use the model to test the likelihood of generating traction depending on the utility the product or service generates for individuals. It is also important to contrast against other factors like date of release (most importantly, the state of market competitors), and thus surveying the combined impact of both. A larger extension of the analysis of market entry time is explored in section 3.4 regarding platform strategy.

The definition of platform properties helps us understand its complex interaction with the products that it offers. As already stated, we may also explore the relationship between platforms, products and consumer heterogeneity. Particularly. address issues concerned with 'blockbuster' formation, market concentration, and the diffusion of platforms. Above all, we focus on the following questions: a) does platform features out-weight the install base of competitors?, b) when do platform features enhance adoption?, and c) how does platform feature composition affect market concentration?. To pursue our survey on platforms' features, we treat the product space of platforms as we have treated game products. So far, we have seen how game features and consumer preferences affect the macro level output of adoption and concentration. The following simulation results address the differences in the system behavior as the features of consoles vary from merely random values to an ideal set of features for consumers (i.e. a feature vector which utility value returns 1).

The general purpose of experimenting with platform features values is to present a comparison between platform growth depending on their own quality (or affinity with preferences) and the previous assumption of complete randomness and noise. After a preliminary analysis of feature effects, we present results on assigning specific product feature values to study the macro behavioral changes when there is a 'better' console. For all simulations we keep two types of consumer agents (as in Extension 1.1) and the developer agents as defined so far.

Preliminary analysis for platform features.

The first benchmark for platform features was understanding how the default features of platforms behave with our two type of consumers (A and B). After understanding the extreme range parameter sweep, we can compare the results with simulations that include different feature compositions. We ran several executions for two and three platforms with the two types of consumer agents. As with the preliminary analysis on consumer segmentation, the simulations where done for several degrees of platform feature similarity.

The typical behavior of the simulations for two and three platforms show several characteristics of the default model. Among them, the usual market concentration with high dominance of one platform while developers maintain a low concentration throughout all simulations. Output parameters like weekly sales, expectation growth, and game releases shares maintain a qualitative similarity and show some consistent effect from platform similarity. One of these effects is present on developers side market concentration. Although platforms' market share does not seem to be altered (with an average HHI of 0.96), publisher agents' concentration slightly decreases as platform similarity grows. The same effect appears with three platforms on the market, with an even higher decrease on the concentration rate. The range of these values went from 0.01 to 0.008 on two platform simulations and from 0.014 to 0.009 on three platform runs.

On another hand, weekly sales present the typical downward slope compared with the first week, but it also comes along a significant volatility. Both, the volatility and slower demand decrease, tend to disappears as platform similarity is higher. Meaning, that platform similarity has an effect on the rotation of games. On this particular case, the difference on weekly behavior can be explained by the positive effect of the platform quality, enhancing the interest and facilitating the growth of weekly blockbusters. Conversely, the negative impact from game features could be taking consumers to find new games. As the expectation growth is consistently increasing (on average and within the range of one standard deviation), we can conclude that consumer agents are not suffering a 'disappointment' shock, so we may incline on the explanation of how platforms enable blockbusters.

Unexpectedly, the output parameter that behaved out of our expectations is adoption rate. Although adopters follow a normal diffusion for each platform, the adoption rate is significantly faster than other simulations. Although we have seen this extreme speed on sensitivity analysis and other experiments, it is not expected to see with the configuration we described above. A possible explanation is that for a portion of consumer agents, the second platform was a suitable candidate and expectation growth kick-started as both platforms are initially equally adopted. After a while the saturation point of one of them is achieved and the other keeps gaining adopters until a critical mass. As seen in Figure 3.8, the difference between the ignited and the flopped consoled is evident two platforms (A) with a larger effect three platform markets (B). On panel A, we see how this happens for three different levels of platform similarity (red = 0%, blue = 50%, and green = 100%) on simulations with two consoles. On the right, panel B shows the same comparison with an additional console in the market. Here, as similarity increases, the ignited console moves

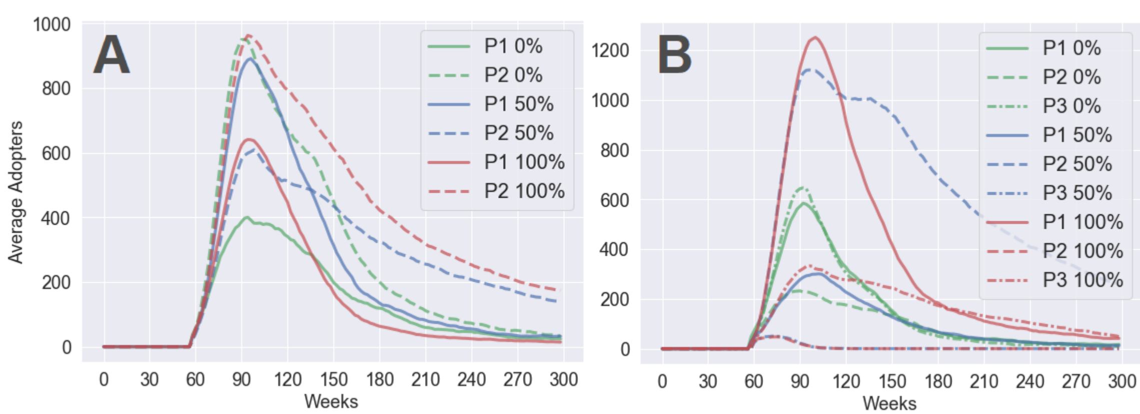

Figure 3.8: Adopters for two and three platforms similarity.

from the last to the first to release, having the second platform to ignite when similarity is on 50% (shown in blue). It is important to remark, for the case of three platforms it is always the platform with mixed features that maintains a larger consumer base for a longer time. Interestingly enough, this effect does not come directly from consumer satisfaction, as expectation is higher for 0% similarity in both market compositions (as shown in Figure 3.9). When platforms are similar, the most likely platform to gain adopters is the first to release. Again, we note how proximity to higher similarity produces uniformity on consumer evaluation, favoring a the formation of a single winner platform.

Expectation growth by itself presents another interesting behavior. When similarity is at its lowest, expectation grows continuously until its peak. Nevertheless, when some degrees of similarity are included, the expectation growth decreases its speed for several iterations until it gains traction once more at week 100. The behavior appears in a simpler pattern on simulation runs with smaller adoption of platforms. The simpler patterns reveals an uptake on expectation until peak and then a slight correction towards a steady state. The case of simulations like Panel A (Fig. 3.9) appear to be formed by two distinctive moments of platform 'ignition'. As simulation have more consoles, the latency of the interruption

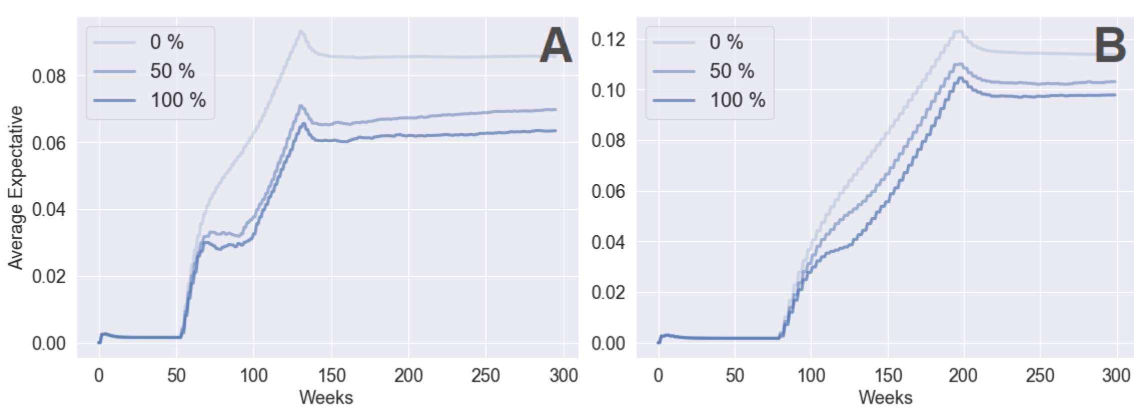

Figure 3.9: Differences in expectation growth.

diminishes (Panel B), and it remains sensible to platform feature heterogeneity. It is important to note that in this last set of experiments, even the lowest average expectation peak and the expectation equilibrium state of three platform runs have higher rates than the best rate of two platforms. Although the effect is lower, we may generalize the description that at higher similarity expectation growth rates do have a slower inflection.

Presenting an ideal platform.

We have seen how the model works when there are two type of consumers and we also surveyed the different output ranges depending on platform similarity. As we would like to know how modeled platform features would gain advantage over competition, we now proceed to survey the relative impact of providing a 'good experience' for consumers compared with the impact of market dominance. In other words, how does platform quality tips the scale in the model. This type of inquiry could lead to understand how an incumbent platform can gain advantage over a 'winner' firm through the mere quality of the service or product. For all the simulations in this section, mass promotion and social influence coefficients were fixed (at 0.7 and 0.3 correspondingly). Ceteris paribus, the survey focuses on the effects of having one platform with an ideal quality for half of consumer agents, while the other platforms remain equally indifferent for all agents. Having the mentioned types A and B, the boosted platform would cater the same values as type A, while the other platforms would have a vector of zeros (being of equivalent utility for A and B consumers). To contrast the possible behaviors we will present the behavior of having the first, second, and third platform as the best prospect. We maintain the same release schedule as in the original model, emulating an almost simultaneous release of all platforms.

First, lets review the results with the first platform having an advantage. Here, the boost in features allows to have an 'upper limit' of the market behavior when there is the great advantage of having the best product and diffusion. This limit also provides a point of comparison for the rest of the simulations. As with the preliminary experiments, market concentration appears consistently high and it slightly diminishes with more platforms. A typical macro behavior of an 'ideal' platform that releases first (although almost immediately) for two platforms is having the second console win over the market (HHI: 0.913) while three consoles runs favor the last one. The defeat of the ideal candidate on the former is related to a slower expectation growth rate, making adoption more likely on a later period. On simulations with three platforms, the fast adoption of the ideal candidate appears to backfire as it eliminates competition too quickly to receive the externalities of their pro-platform mass promotion. Thus, making this typical run output the smallest market among all other initialization, even when it has more platform agents. The two console counterpart achieves an average peak of 1810 consumer adopters, more than twice of the typical consumer side on the case of three.

The second case had the same initialization configuration but the 'ideal' feature values where given to the second platform (in order of release). In this case, we see how quality may overcome the advantage of early entry. Similar to the first console experiments, there is an even higher decrease in market concentration. What is remarkable for this composition is the rise on publisher or developer agent market shares (an increase of the HHI from 0.009 to 0.015 on average). Simulations with two consoles between the first case and this one are similar but present interesting differences. The total amount of consumer adopters reduces to an average around 1200 (approximately a 40% reduction). But, even though its peak is shorter, in this case it is also the platform with the best utility. Thus, the dis-adoption rate of the second platform is slower and typically amasses over 48.1% of the consumer population, compared with the first entry as best console where the consumer side usually encompasses 37.20%. Additionally, considering the complex relationship between platforms, we see that the first platform temporarily gain more traction kick-starting the expectation growth (only to be surpassed soon after by the second console with full affinity). For this case three platform runs (seen in panel B in Figure 3.10), we see how it is not the second console that wins over the market, but the third. The average saturation in this case is lower than with only two and the last being the ideal one, having an average 35.56% of total adopters. Again, the smaller size of this market may be explained by the presence of other platforms and the place that the best console uses. When we have three platforms, expectation appears to grow faster. Additionally, the quality of the second platform can further improve expectation within the population. This combination of 'hype' finally is reaped by the third platform, which releases later with the ongoing adoption of the consumer population. Already this computational example has shown how the advantage of the best possible platform is not robust to the externalities of other platforms' promotion.

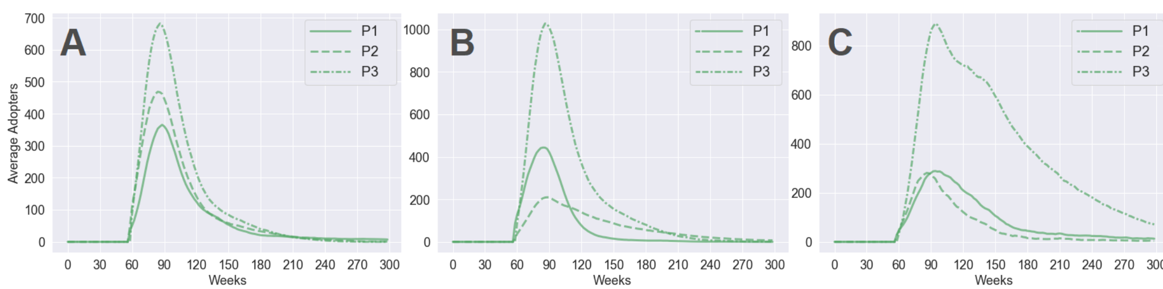

Figure 3.10: Best quality versus release order.

The final case considers having the last platform with the best features for consumer type A. In this case, we only went through simulations with three platforms. As expected, many output parameters behave like the preliminary analysis surveyed. Now, the market presents a high saturation with 82.14% of consumer agents adopting the platform at any given point. Consistent with previous results where the third platform ignites, we see a swift growth that is not accompanied by the usual drop. Instead, there is a minor decay and recuperation before slowly decreasing. Furthermore, this is the console with better quality, providing a robust expectation within a large consumer base that sustains the longer period of platform activity. Figure 3.10 presents the results of having the best console release first, second and third (panel A, B, and C respectively). An important remark is the difference between the 'winner's adoption peak and its competition. This gap grows bigger as we change the entry order of the best platform. We also see how in the last experiments the winner is able to maintain the consumer base, as mentioned above. In general, results suggest that being the last to ride the 'hype' is important when platforms release virtually at the same time.

Following the work done on these experiments, we attempted to put attention to the insurgent platform. In the general model (chapter 2) there is a strong tendency towards first mover's advantage. Accordingly, we now try to assess (under the premise and assumptions of the model) the effect of platform features. In accordance to our questions, we would like to assess the systems' parameters. Simulations that have a second or third platform with ideal product features show that quality can be a factor of relevance above entry advantage. Regardless of being an experience good, the platform is ultimately evaluated by most consumers as it is a requirement to access games and there are at most 3 of them.

With the results so far we can answer to the question about how does platform feature composition affect market concentration. As we see, it does play a role on settling a definitive winner, or in other words, it significantly contributes to the adoption of platforms with a 'winner-takes-all' output. Platform features show that publisher concentration may be affected but without a powerful uptake, it merely suggests that at higher similarity we can expect lower game sales concentration. We can also address the issue about platform features out-weighting the install base of competitors. Although further analysis of entry time is presented below (Extension 3.1), we already know that - under the models assumptions- being the best console is not always beneficial. Timing, considering the co-evolution of diffusion and side participation, is critical for platform analysis. Such as these results, counter-intuitive phenomena are common in platform behavior. Take for example the consequence of being the (extremely) best console, where the platform benefits the competition as it raises consumers expectation; or the example of feature similarity, where those not too similar but not too different seem to ignite larger markets. This takes us to the second question mentioned in the beginning of this section: when do platform features enhance adoption? Again, it appears fundamentally interconnected with other aspects such as uncertainty and market composition. Nevertheless, better utility does drive higher expectation and adoption, which does not mean that system-wide this is going to endure. The revision of game goods properties would be an important relationship to understand for further studies using this approach.

3.2.4 Extension 1.3: Mixed behavior with 'ideal' products.

The last set of experiments for the feature and preferences extension includes the definition of a general product that targets a specific consumer agent type. As with the platform features and previous analysis, the idea is to assess the effect of products features over a defined consumer base. In this case, the specific objective is to survey behavioral and output parameter changes when game publishers target one type of consumer. Once again under the models limitation, we are able to address the extreme values and scenarios for game producers depending on the selected target. Although is highly relevant for platforms (when their service or any side's product include these properties), this has been the particular challenge of entertainment business entrepreneurs and managers: the evaluation of the audience's response depending on their product's design. To begin the exploration of this topic, we present a set of preliminary analysis and experiments to determine the possible variations. Considering the relevance of traceability and of having clarity on agents behavior, experiment 2 and 3 follow specific developer firms and groups that share a targeted product (i.e. with matching values with target consumer type preferences).

The three types of consumers are represented in same fashion as before. , instead of having two halves consumers now have a third of 1s and 2 thirds of -1s, meaning that not all agents are mutually exclusive as before. (3.1) didn't include overlaps on preferences, now we may begin to test the outcomes of consumer heterogeneity and similarity. This theoretical exercise contributes to the revision of non-linear behaviors between consumer composition, product's attributes, and market performance (i.e. shares, sales, amount of releases, and firms). For almost all experiments in this section, developer agents are given product feature values that fit one of these consumer types. Posterior simulations include segments of developers and the performance of a sole ideal developer agent.

Preliminary experiments for targeted products.

As products have been defined by uniform distributions, developer agents and their products have no impact. The particular advantage any product or agent may gain depends on their environment, meaning that the diffusion of consumers' opinions or the dynamics of platform's size are the ones that mostly determine their penetration. We now may assess how much advantage do products with high utility gain compared with random utility products. First, we run experiments to provide a baseline behavior of three types of consumers with the initialization configuration of the default model. As expected, most parameters and behaviors follow the usual patterns. Nevertheless, there is a significant change in the formation of expectations on two platform markets, where average expectation falls immediately after release. This behavior is produced due the high utility required for the rigid types of consumer agents to maintain a positive attitude. The requirement makes platform adoption unlikely in an environment of low promotion (as word of mouth will not be enough to build hype). On the other hand. when there are three platforms on the simulated market, promotion is enough to ignite one platform (the first to release). Overall, the baseline experiments take our attention to the ignition problem when there are more types of consumers. The hard conditions for games' success (and the consequent support to platforms' performance) required us to survey a less harsh scenario. We modified product features values to a full vector of negative ones. These values are identical to most of consumers preferences among all types (as each agent has seven preference traits set to -1). Thus, these experiments test the market's behavior under products with positive utility, but still considering that each consumer type valued a different element of the available products. Under these conditions, the behavior shifts to resemble the typical behavior of the original model; including the development of expectation. On this particular case, expectation perceives a higher growth rate and maximum. The adopters series show how the first release captures the market in both scenarios, but having a saturation peak of almost 5 times more (near 35%) in the two platforms scenario. It is clear how in the other case, platforms with lower quality potential dragged the expectation down, affecting the success of the targeted platform.

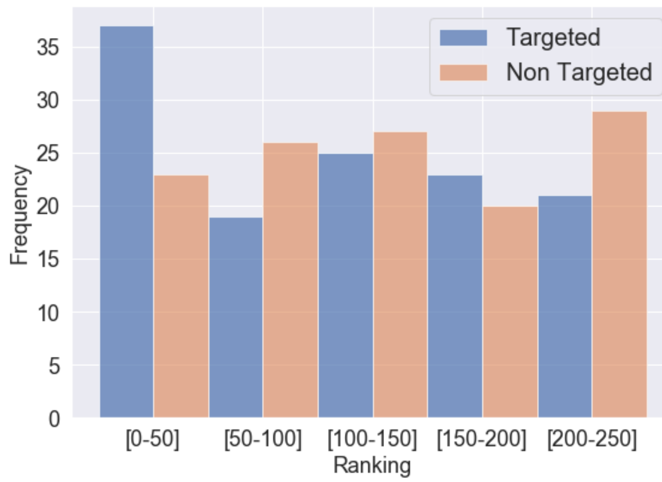

Figure 3.11: Final ranking for targeted and non targeted developer agents.

As we put our attention to targeted products, we tracked the rankings for publisher agents during the simulations of this section. The average rank for developer agents that had targeted products were 108.88 and 142.12, for two and three platforms respectively. Although the standard deviation is relatively high (72.31 and 67.83), this statistic usually presents extreme values depending on the simulation conditions robustness. Thus, on experiments where ignition may not occur, the results are difficult to interpret (even more when there are many platforms and some do not achieve critical mass). Using values of the average rank per simulation for targeted and non-targeted, we proceed with a Student T-test. Accordingly to the typical average, targeted products do have a significant impact on the ranking difference. Publisher agents that developed for intersecting preferences of consumers present an advantage over the uncertainty and noise of the modeled market. As we know that in regular markets (i.e. search goods), quality usually drives sales and the possibility of segmentation and price discrimination. We would expect the same behavior on experience goods markets and also in the model's representation of these behaviors (as consumer change their expectations based on the product traits). Although the advantage is significant, this does not happen every simulation and for every developer. Figure 3.11 shows a histogram with average of ranks, the distribution shows how targeted firms do not appear to behave different from non-targeted on lower ranks. A clear effect of the product features are the top 10 firms. The concentration on the top tiers without being absent on the other ranks confirms that is not only a matter of quality. It is important to note that those with uniform product features are slightly more likely to end up on the lowest tier. The final ranking is modified by simultaneous behaviors, among them we find that the 'preferential attachment seen in blockbuster behavior and described on chapter 1 are contributing to the targeted firms success. It is in a combination of quality and hype that renowned and successful firms find their most important stepping stones. The behavior on rankings is similar on three platforms, where non targeted suffer a slight decline towards worst rankings. After this preliminary analysis, the model results indicate the general behaviors that follow the inclusion of additional types and products that target them. The following section goes over simulations with only one consumer type as target, indicating the major differences of this approach.

Targeting to preference minorities.

The behavior seen in the previous set of experiments represents the known strategy to appeal to many consumers. Following with the initial remarks on consumer preference and segmentation, firms on entertainment markets usually cater most consumers they can with common traits and also selecting different traits that could cater different sub-segments or sub-cultures, attempting to amass the maximum amount of potential consumers. Platforms usually contribute to discriminate on the preferences of consumers as well. Along with the selection of shared preferences, firms also opt for limiting the audience for a better appraisal or for the cultural or artistic intent of the company. To contrast the behaviors of these strategies, lets go over the results of experiments where the 'ideal' product is tailored for a minority; in this case, targeting one of the consumer types. For what we know of entertainment markets, we should expect that selecting a minority is only viable if the selected group is going to appreciate the value of the product. Otherwise, attempting to gain a broader audience could appear more prosperous. The model is limit in its representation of fanatic groups as a defined entity which maintains its organism properties through time (i.e. usually there is identification, values, roles, and defined community), the model only recognizes the formation of such a group through the unorganized appearance of clusters. The latter are very sensible to additional degrees of separation, meaning that changes on the friends of friends expectations can affect the cluster losing the characteristic robustness of a fanatic group. Thus, we can previously infer that model will not be able to represent this phenomena that plays a critical role on targeting minorities. Nevertheless, the inspection of a such a behavior gives hints on system conditions that could benefit this strategy, and also reflect on situation where it may have an advantage.

Results indicate that the first condition that heavily shapes the success for minority targeting firms is the composition of the platforms market. We've seen so far that the number of these indistinguishable platforms affects drastically the adoption of the winner that takes it all. In this case, the first of two platforms gains a similar advantage compared with the previous experiment; reaching up to nearly five times the total adopters. When we have three firms, adoption is truncated and the last platform is almost unable to ignite. The average diffusion for two platforms goes to a single victor that overwhelms competition regardless of incurring in a lower expectation growth (Panel B). The strategy of selecting only one type of consumer does see a minor change on its effectiveness compared to the majority approach.

Overall, the selection of a broader or narrower audience is highly dependent on the market conditions. Ceteris paribus, the model outputs reveal that targeting mainstream audiences does have an advantage over minor segments. This behavior does qualitatively represent one of the entertainment market fundamental strategies. It also raises the question concerning current and future entertainment platforms where these strategies may have different outcomes if publisher firms have an impact on the market. Meaning that, as seen on the simulations of targeting strategy, if there are enough firms that choose a type of strategy they could affect the eco-system of platforms.

3.2.5 Insights on Extension 1.

So far we've seen how the model responds to some abstract changes regarding population, game product, and platform properties. We've seen how the macro behavior of the simulated market changes as we take previously absolute random properties and place some hypothetical distributions. Among these scenarios we became aware of similarities at a population or group level can affect every parameter of the simulation without affecting the typical trend of behavior. Usually, when the life-cycle process of the market changes, it is because ignition was not achieved. The model's consumer counterpart, the product and platform features, also reveal substantial effects on their own right. An interesting phenomena that we see in both products is the non-linear relationship between products similarity and market size, showing that some similarity is valuable but including heterogeneity is ultimately better. Another interesting finding about the relationship of platform quality and game sales, is that at a higher platform quality enhances blockbuster formation with weekly sales and market shares becoming more skewed. On the other hand, being the best platform or game product doesn't necessarily payoff. We have seen that for platforms the relative advantage of releasing at higher market expectations overcomes the relevance of quality. Similarly, for game products, the distribution of final sales for ideal games does indicate a slight advantage (or a higher probability for becoming a blockbuster) but in general behaving very similar to games with random features. Following with the results so far, it appears that in a market with high uncertainty, externalities or indirect network effects between agents makes the system very challenging to understand by its separated parts. For example, the indirect network effects of consumers on developers was expected at the moment of designing the agent-based model, but effects of product attribute distribution on the macro parameters of platform activity or generation longevity were not expected. These results are encouraging to pursue a next iteration of consumer and product model that could address the relevance of quality in experience goods markets.

3.3 Extension 2: Consumer Evaluation.

On previous chapter we have discussed the relevance of cognition and socio-cognitive processes when modeling consumer behavior. For the purpose of the agent-based model design, the minimal representation of an heterogeneous individual with bounded rationality was the objective. Although this is also for the sake of the model's parsimony, it falls short to represent other relevant behaviors. There are many approaches to cognitive processes including models and architectures to represent them [Chipman, 2017], each with a different focus. Among the many types of processes of cognition, the overall process of perception and decision making with scarce information are the key behaviors that are at stake in our target system. Uncertainty of experience goods is based on a set of core features that are difficult or impossible to evaluate a priori. Perception is broadly defined as a sensory driven process; which includes a top-down mechanism of relating new information to previous knowledge. The process of aggregating this new information is fundamental for individuals to evaluate new products, as it is the basic process through which we make decisions. We then model consumer perception as the capacity to relate new and partial information with their own preferences. This process is not considered to be either conscious or unconscious. Thus, the following extension considers the implementation and analysis of the consumer agent's capacity to partially evaluate the product's features before consumption or adoption. In terms of our economic definition on cultural market's products, we break into a fuzzy area between experience and search goods. Having this capacity at maximum would mean that agents know their utility before their decision to adopt.

Perception is implemented in the consumer class as an additional function that estimates utility based on a random but fixed sub-set of features. As a parameter, perception capacity is a value between 0 and 10, representing the amount of vector components the perception function will consider to calculate utility. A perception capacity of 10 means that the agent will know the identical value of utility given after purchase, when capacity is at 0 agents can't get a sample to estimate it (i.e. behaving as modeled so far). On another hand, perception does not occur every activation or for every product. Once the agent has decided to select the best prospect to purchase through peer's recommendation or mass promotion, it attempts to estimate the utility of the most desired products. Originally, agents would adopt the best expectation blindly; now, agents evaluate the top five games of their interest (i.e. the highest five expectation values when the agent has passed the adoption threshold). Starting from the highest expectation value, agents will estimate utility, if it is positive they will purchase the game; if not, they'll try the next one. For example, let us say that agent A has a perception capacity of 3 from the total ten features. During the simulation, if the agent has adopted a platform it will attempt to purchase its top game (i.e. the highest expectation value among games). When estimating, the agent will have three components to get the values from the product features vector and its own preferences; the locations of these components are fixed and established at random on the agent's initialization. In this case, the agent attempts the known utility function (Eq. 2.14) to the sampled vector. A positive value would mean that the agent purchases and then, to determine the actual utility, it evaluates again with all values. It is important to note that the whole process of perception occurs only when social influence has signaled expectations. This is why even with complete perception, the selection of products does not represent or behave like a search good [Nelson, 1970].

3.3.1 Preliminary analysis.

For the preliminary analysis of consumer perception we provide four benchmark experiments. Each benchmark surveys the typical behavior of the specified conditions for one to three platforms. The first experiment provides clarity on how the model behaves when all products and consumer preferences are the same. Although agents still form their expectations by social ties and positive promotion, the agents' perception utility and high praise generates a positive feedback of growth. To understand the upper limits of this growth, we present some experiments laying them out. After that, we insert some heterogeneity to game features which results in perception noise for the consumer agents. For the second set of experiments, the scenario consists of products having half of their features as negative ones (where we would expect utility to be 0). Finally, we present the impact of perception on simulations with capacity values set on 0, 3, 6, and finally 9 vector components. This third set of experiments is then compared against results with perfect products. A fourth set does the same but contrasting the perception effect with faulty products.

Behavior with perception and ideal products.

Results of the initial simulations of the first benchmark reveal the market's behavior with absolute similarity and ideal fits between product features and consumer preferences. Figure

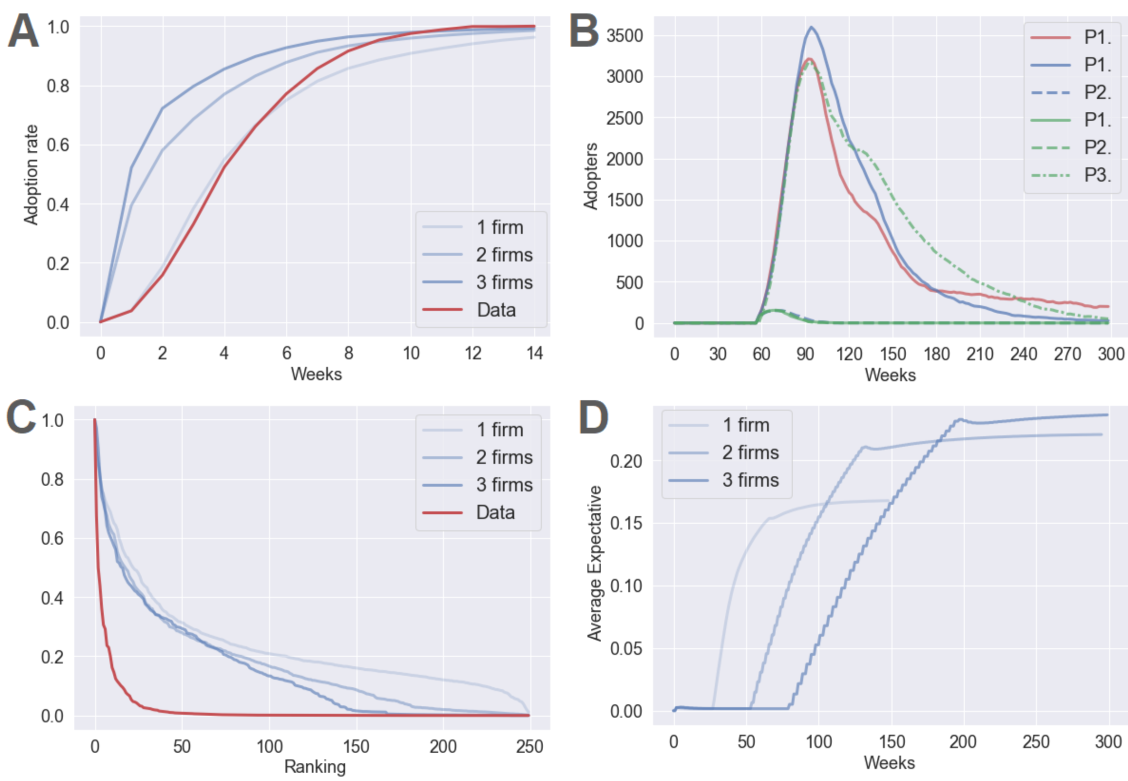

Figure 3.12: Overview of the default model with high rewards.

3.12 compares how expectation, adoption rates, and publisher sales change depending on the amount of platforms included. The behavior of the market follows the typical performance described on the model's calibration. After one platform, which reveals the typical patterns, other simulations show an enhanced adoption rate (similar to those seen in Extension 1). The higher adoption rate is also correlated with a more concentrated publisher market, a higher expectation growth, and usually a slightly better total platform penetration. Interestingly, the simulations of three platform markets had a divided outcome; some ignited with a total adoption similar to the winner platforms in other experiments and others see the three platforms market with only minimal platform activity. An explanation for this behavior resides on the excessive diffusion (via social influence) that an ideal platform and games would have in an environment with more promotion. Such an invasive hype would be detrimental to platforms as all agents select at random among this highly promoted portfolio. Thus, as many platforms get more adopters consumer begin to segregate and share less relevant information, busting platform activity on the short run. This would also explain the speed of adoption rates seen in Panel A and D (Figure 3.12); where higher platforms actually develop faster but sometimes only to flop altogether. Simulations with only one firm are slower in adoption (although adjusting to the typical curve seen in the data), accumulate less average expectations, and usually sell less games and consoles. They also show a thick tail in publisher distribution, with a higher inflection of the distribution towards the end of the head. Two platforms runs already see a leap to faster adoption, similar game sales distribution, higher average expectation, and with a more robust behavior on ignition. Different from many simulation outputs, the typical winner does not correspond to neither first or second release; they are both equally likely. As shown in the figure, for the case of three platforms it is usually the third console that ignites on average. This is also evident in Table 3.1, where the statistics of adopters for three platforms shows the highest mean and standard deviation. Columns show the statistics in order of console release [1]. Meaning, that although there is some volatility, this is usually the console that captures more market.

[1] Text in bold denotes consoles that will most likely dominate the competition

Table 3.1: Mean and standard deviation for adopters of 1, 2, and 3 platforms.

Platforms	First	Second	Third
1	M: 935.4, SD: 1326.95	-	-
2	M: 470.7, SD: 666.78	M: 444.51, SD: 615.99	-
3	M: 27.65, SD: 42.33	M: 197.88, SD: 264.19	**M: 529.457, SD: 748.71**

Another set of experiments were run to contrast the results of the previous simulation outputs against the inclusion of perception capacity. We executed the same configuration for ideal products with the default initialization but including several levels of capacity. Results include the market outputs for perception degrees on 30%, 60%, and 90% of their own preferences and corresponding features. Results for one platform show very consistent outputs, where the sole platform usually ignites and achieves higher penetrations as perception increases. Simulations with full ignitions gain up to 33.9%, 35.12%, and 37.8% for the mentioned levels of perception respectively. Expectation also sees an increase up to twice its value between the lowest and highest setting of perception capacity. On other parameters like adoption rates, publisher market share distribution, or weekly sales, the behavior is consistently similar between all different perception levels. Meaning, that perception shows an effect over total expectation and consumer adopters size, but it does not affect competition of games or the speed of adoption.

Simulations with two platforms and several degrees of perception capacity indicate a high uncertainty on platform ignition. Immediately we perceive the increased adoption rate given the amount of promotion rise. This boost on promotion is expected as seen on the previous experiment. At a higher amount of platform firms we also see a faster adoption rate. Although most of the parameters keep a relative similarity, the major difference for the experiment runs with two platforms and some perception is the probability of ignition. Once again, with more platforms the likelihood of having an active platform decreases,

Table 3.2: Mean and standard deviation between perception capacity levels (3 platforms).

Perception	First	Second	Third
30%	**M: 317.79, SD: 440.62**	M: 15.65, SD: 21.47	M: 270.51, SD: 391.56
60%	**M: 195.66, SD: 276.47**	M: 17.04, SD: 23.44	M: 36.41, SD: 48.86
90%	M: 209.09, SD: 290.99	M: 208.88, SD: 281.82	M: 529.457, SD: 748.71

augmenting the amount of cases with no markets. Finally, simulation with three platforms extends this behavior further. Adoption rates are even higher while the rest remains similar. Following with the likelihood of ignition, the three platform market provides interesting results. As seen in Table 3.2, the average sales for platforms tend to favour the first to release on lower levels of perception and, occasionally, tip over the third to release when perception is high. The lowest perception capacity tested provides an interesting output where the first and last platform to release are able to ignite with a substantial penetration. With an increment on perception, the first platform maintains its advantage while others stay on minimal and no ignition at all. For a large perception capacity, the third platform to release gains an advantage on its market impact. Although we see the same volatility as before, the first and second consoles show that one standard deviation above of their mean would still be below the average output for the last console.

The experiment runs that include perception capacity on three platforms have a notorious increase on adoption speed and positive correlation with expectation growth. On Figure 3.13 we see on Panel A the shifted adoption rate, that follows what we saw on the benchmark outputs (Figure 3.12). The distribution of game sales generally follows the distribution of three platforms markets but with a longer and thicker tail. Albeit the similarities, the volatility of markets with perception provides new ranges of behavior for the consoles. Panel B on Figure 3.13 illustrates this phenomena on one of the many simulation

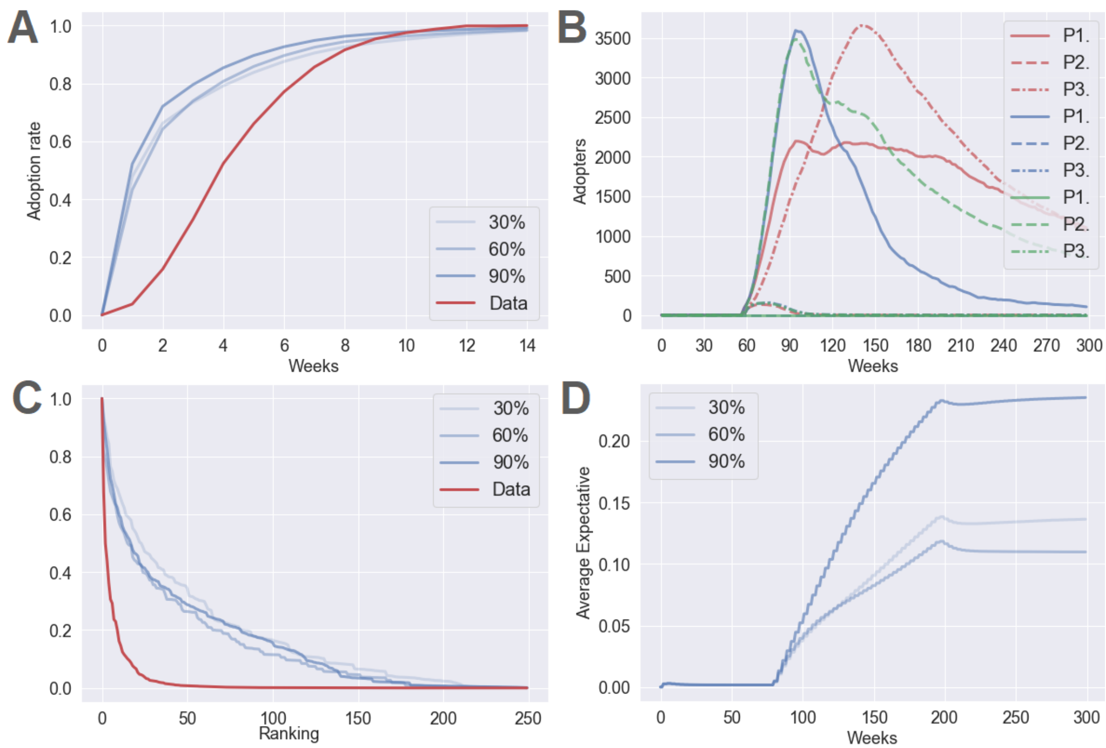

Figure 3.13: Overview of perception values with high rewards (3 platforms).

outputs. Agents capacity of 30%, 60%, and 90% are respectively displayed in red, blue, and green. Here, we may appreciate how different patterns of adoption arise; particularly those with the lower levels of perception that have a smaller roof of adopters with a slower but larger platform activity.

Perception behavior with mixed product features.

Now that we've surveyed the behavior of ideal products, let us review the impact of mixed product features. After an initial inspection, we can determine that the inclusion of mixed products slows expectation growth (Figure 3.14, Panel D), which makes sense as there are several more instances for the agent's virtual disappointment. Additionally, this slower expectation rates facilitate the development of a winner platform. Although this process builds hype and consolidate a critical mass, the fuzzy and volatile behavior usually means that platforms do not ignite. The worst case is for runs with one platform, as the lack of ignition means there is no market at all. Table 3.3 presents averages and standard deviation values of the general outcomes for the first, second, and third console in the three platforms scenario. The results variance indicates the volatile behavior between the best platform penetration to several simulation outputs without ignition. Similarly to the results on high rewards (i.e. when features and preferences have a utility of 1), we see how three platforms markets usually have their third to release console as the winner. In this case, regardless of the volatility on ignition, it is the third platform that has a clear advantage over the others. When having two platforms in the market, we also see some effect from the reaction to mixed products; the first to release platform has a significant advantage on their likelihood to ignite and dominate the market.

The behavior with mixed products generally resembled the outputs of the default model.

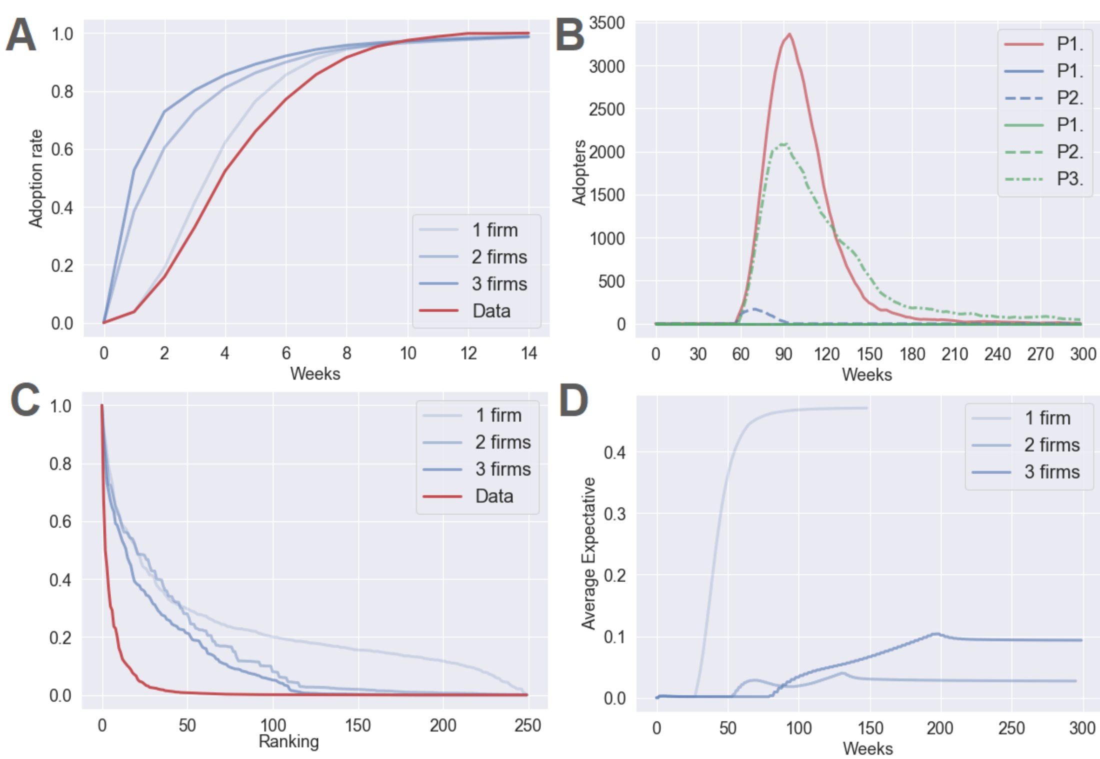

Figure 3.14: Overview of the default model with mixed rewards.

As expected, when there is only one platform the behavior does not change much, similar to runs including high reward products. On two platforms markets, the results favour different release dates according to perception capacity values. With 30% of perception the first platform usually dominates with a mean of 233.77 adopters while the second to release has an average of 13.05. At the next range of 60% of capacity, the second console shows a higher likelihood to succeed (M: 279.09, SD: 387.07) over the first one (M: 140.48, SD: 175.26). Average outputs on three platforms provide new probabilities of ignition and general market behaviors. Table 3.4 shows how throughout all levels of perception capacity the third platform to release typically has an advantage. So far, we've seen this type of behavior on simulation where hype allowed the third platform to gain advantage as a tardy opportunity for slower adopters. In this case, mean and standard deviation values on adopters indicate how the third platform clearly dominates on 30% and 60%, while having an advantage on 90% of consumer perception.

The differences on the three platforms market scenario go beyond this increased likelihood for the third console. We also appreciate a shift in platform adoption behavior from the usual peak at 90-100 steps (Figure 3.15, panel A) and later ignitions with three platforms scenarios (on C). Furthermore, the underlying behavior of expectations between these two market compositions are starkly different, as seen in Figure 3.15 on panels B and D. The scenario of two platforms shows how perception increasingly benefits the expectation growth starting from a negative formation at 30%. On the other hand, scenarios with three consoles show the reverse effect. Where lower perception values contribute to

Table 3.3: Mean and standard deviation for adopters with mixed products.

Platforms	First	Second	Third
1	M: 846.7, SD: 1176.1	-	-
2	**M: 167.09, SD: 218.7**	M: 15.29, SD: 25.93	-
3	M: 4.85, SD: 9.67	M: 5.6, SD: 10.40	**M: 398.36, SD: 537.85**

Table 3.4: Adopters among perception levels with mixed products.

Perception	First	Second	Third
30%	M: 120.29, SD: 440.62	M: 114.82, SD: 153.26	**M: 203, SD: 295.04**
60%	M: 9.14, SD: 18.08	M: 17.37, SD: 31.64	**M: 360.66, SD: 496.22**
90%	M: 209.09, SD: 290.99	M: 208.88, SD: 281.82	**M: 529.457, SD: 748.71**

higher expectation growths. Again, we see how the excess of promotion by many platforms can generate an undesired effect of expectation drainage. Too much promotion takes more consumer agents to evaluate, lower perception maintains the uncertainty and consumers

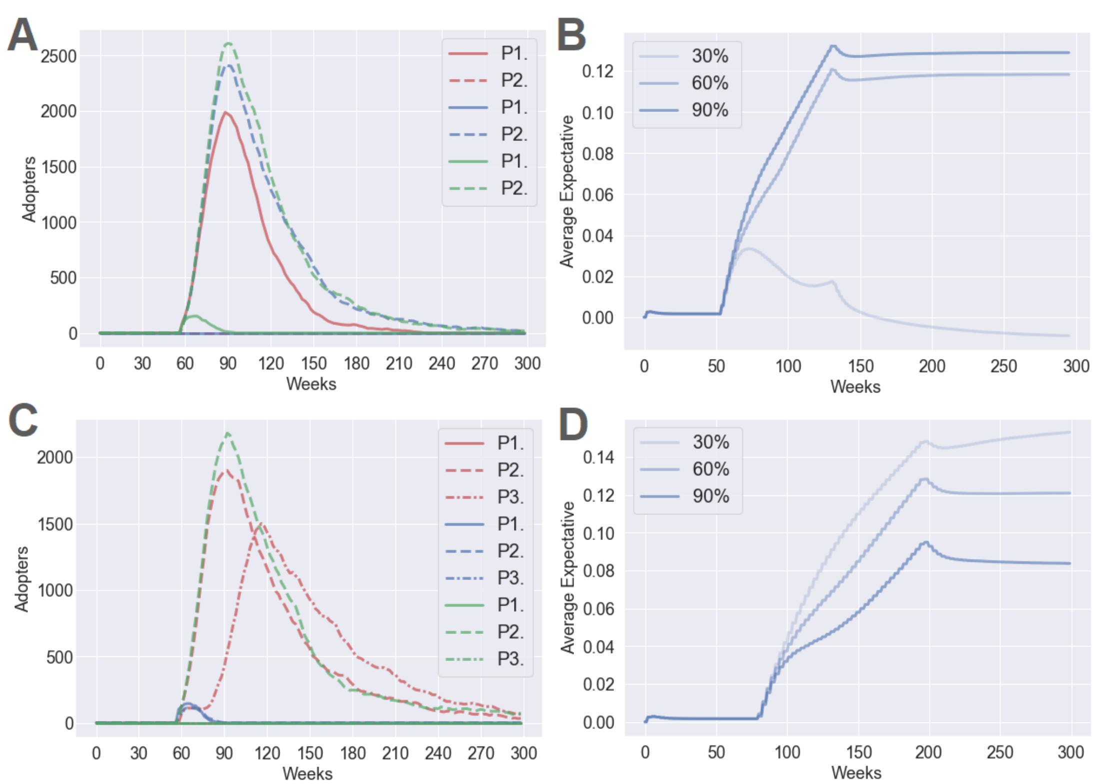

Figure 3.15: Comparison of two and three platforms scenarios with perception.

still purchase, usually giving incentives to others and providing incentives towards the full ignition of the platform.

Perception with mixed and high reward products.

The purpose of implementing perception is to evaluate the effect of partial information at the moment of a purchase decision. So far, we covered ideal products (i.e. preferences and product features being the same) and mixed products (i.e. where some preferences are catered). For products with high rewards, higher perception generates an effect of early adoption (usually towards the first platform). On the other hand, high perception capacity with mixed products usually favors a late adoption and the success of later releases. Now, we proceed to present the results of a market scenario where mixed and high reward games are equally likely to be developed. Results of the initial simulations showed that perception plays an important role on the growth of the market.

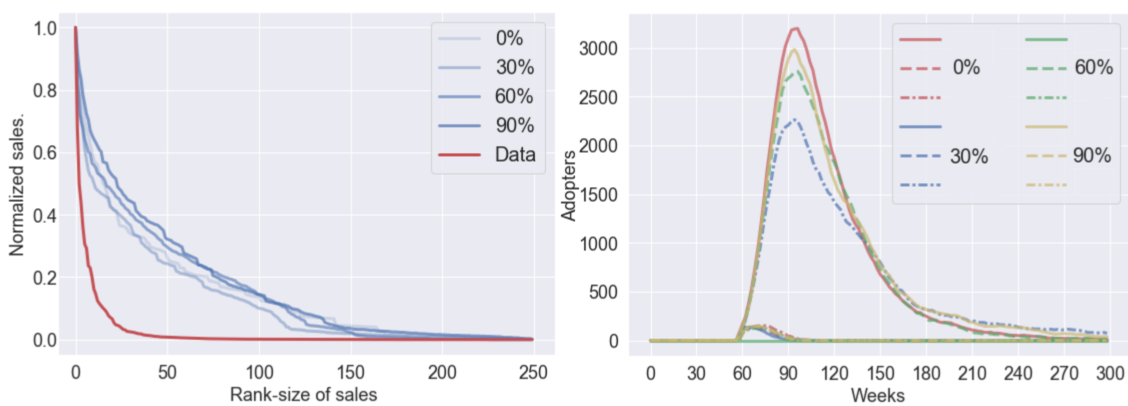

Figure 3.16: Perception effect on adopters and publisher sales (3 platforms).

For the scenario with three platforms, even if all products would have ideal or mixed properties, the tendency towards growth remains. Overall, as perception increases we see how platforms activity correlates positively. An interesting behavior appears on 0% perception where some simulations have the first or third platform (average adopters on 354.45 and 180.16 respectively) with the largest market size among other perception levels. Market concentration remains relatively similar for all levels of perception on these settings, having platforms to remain with an average HHI of 0.92 among all experiments. Publishers also have a similar concentration for all perception values, this is also evident on the publisher sales distribution seen in Figure 3.16. As an additional note to keep note about the persistent effect of disappointments, it is recurrent to see that the later platform receives higher participation when the likelihood of negative utility is higher; or in other words, when expectation does not meet the reality of features over preferences.

3.3.2 Insights on Extension 2.

Similarly to extension 1, the inclusion of consumer perception provides a non-linear interaction between the new parameters and the simulations behavior. Perception can play along with the development of more platforms maintaining high expectation throughout the market cycle. Nevertheless, depending on the relationship between preferences and features, the amount of promotion, or even the natural social hype, can play negatively role when consumers can evaluate partially. The simulation results confirm a typical behavior when following mixed products. If there is a possibility of consuming the wrong product and there is no perception, expectation falls to a negative value. On the other hand, complete lack of information leaves the social influence engine work through the detection of quality products. In general, the inclusion of an a priori evaluation shows that consumers form better expectations when they may evaluate the products (as it should be expected from this type of behavior) but plays an ambivalent role for platform formation. If product uncertainty in the market would only be present for publishers (i.e. only producers would 'not know anything') the market has a higher probability to fail. We would assume that in the real market, if consumer have a better understanding of products, producers would also be able to design them towards a better quality; countering the negative effects and indirectly promoting a healthier platform market.

As we know, consumers on the video game market are able to try or evaluate part of the game products before buying (e.g. playing a demonstration or at a friends' house). An asymmetry on product evaluation for the two sides of the platform (e.g. consumers having a better capacity to evaluate a product over game developers) ultimately generates a scenario where -for better or worse- consumers know best. The case of Atari's fall and the 83's market crash based on poor quality is an instance of this situation [Hagiu and Herman, 2013]. Here, producers blindly offered products that consumers could consistently evaluate as worse than acceptable, leading to negative expectations and the dis-adoption of basically the leader platform (a loss of expectations that ultimately affected all other minor competitors).

3.4 Extension 3: Platform Management.

Last but not least, we refer directly to aspects of the market that worry platform managers. This extension pays attention to other behaviors and dynamics present in the target system that are not directly involved with product's features or how the consumer's composition contributes to tip the market. We've already seen how different platforms features or the amount of platforms in the market affects the simulation's output. Following the concerns mentioned in the beginning of the chapter, we refer to the effects of entry time, multi-homing, and a platform's management of side participation. As with previous extensions, we present the modifications around these topics over the base model presented in chapter 2.

The evaluation of entry schedule effects in the target system is complex and many confounded factors are involved. Given the competitive console market and the winner-take-most dynamics of multi-sided markets, if the platform's fate it not known before the release, it is usually determined within a year after release. We present an analysis of entry times for platform competition using the agent-based model. We address their effect on market concentration, gaining advantage over the competition, and establishing a healthy environment for platforms to ignite. To go over these changes, we present a systematic modification of release dates for platform agents, providing a comparison of the different simulation outputs following the entry time parameter. After the revision of entry experiments, we present the extension on multi-homing behavior; allowing developer and consumer agents to adopt more than one platform. Finally, we present how strategies on license management, game titles exclusivity, and consumer price affect the market simulation.

3.4.1 Time of entry.

The particular moment to release or announce a new endeavour as a platform may have large repercussions on the firm's development. The conditions of entry could be beneficial or not depending on the situation, even beyond the consideration of the competitors' state or a particular advantage (e.g. better graphics or processing power, in the case of game consoles). As we've seen so far, the model is very sensitive to entry order; after some experiments we noticed that the variable of platform release could modify macro behaviors concerning the parameters we've been analyzing. Changes on the market dynamics given the entry of platforms do have a long term impact and generally adjusts the scale of the simulated market, adoption rate speed, expectation formation, publisher market share, and the duration of platform activity. The exploration of platform entry times was performed by the inspection of release dates separated by a financial quarter; meaning that for each additional experiment, subsequent firms after the first one have an additional 12 weeks until they release. In the case of three platforms, it would release 24 weeks or simulation steps after the first one. We do this for a gap of 12, 24, and 36 steps.

Results with a 12 steps gap.

The initial exploration of a single gap on release dates already gives important insights on the macro behavior of the platform ecosystem. The most affected aspect is platform participation. Consumer agents reach up to 40% of participation on platforms while also achieving a 30% of adoption on previous platforms (i.e those that release first). The effect is most noticeable on the three platform scenario, which is expected given the known boost on platform promotion. On the right panel of Figure 3.17 we appreciate the jump-start

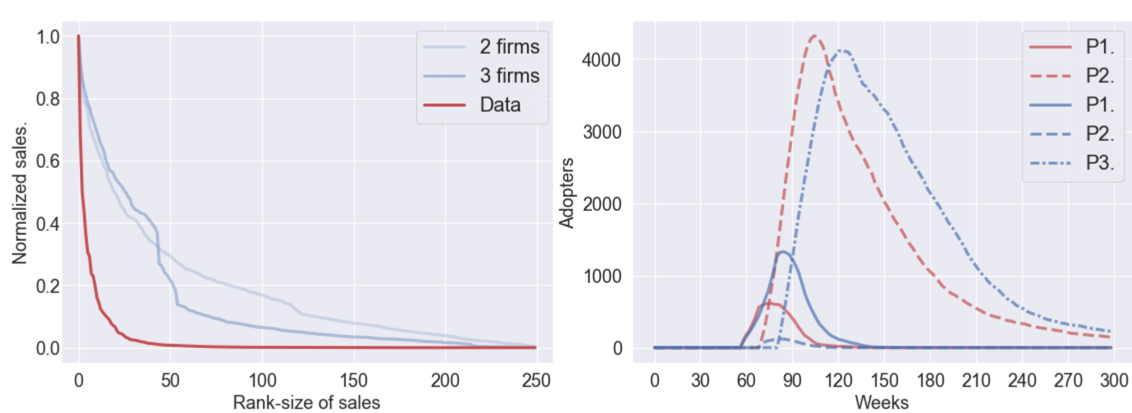

Figure 3.17: General behaviors with a 12 steps gap between releases.

that the second platform (and the third in the case of three platforms simulations) receives from the previous firms. Although with more platforms expectation rates suffer in growth speed, this scenario opens the market to a wide audience and doubles the amount of sales for publishers. At the same time, the market concentration of the publisher side is affected. The tail of rank-sized sales is truncated leaving the top 50 publishers with an usually unequal share of the market (Figure 3.17). Another significant difference with previous simulations is the concentration seen on three platforms (HHI: 0.49). As the gap allows to take different states of the same consumer and the competition is diversified trough different moments, it is possible to see the coexistence of platforms due to multiple ignitions.

Results with a 24 steps gap.

Simulations with a 24 steps gap show a slower adoption rates in general. Given that platform stay more time active, the general adoption curves follow closely to those seen in the target system. We see how more platforms generate a longer active period, consumer adoption rate and dis-adoption gets slower; even below the empirical typical rate. Beyond this change and the ones noted below, the experiments on 24 steps gap between releases does not show significant differences on macro behaviors. The differences with the previous entry schedule appear on a matter of degree. On 12 steps, we saw how later platforms reached high market

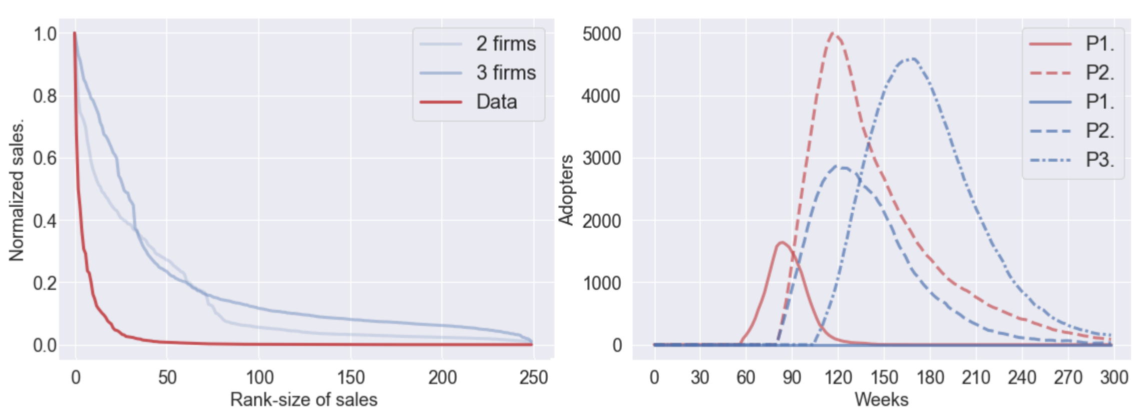

Figure 3.18: General behaviors with a 24 steps gap between releases.

penetration, while in this case it reaches up to 50% (e.g. P2 on the two platform scenario, Figure 3.18 in red. On the other hand, publishers sales rank-size maintains the effect on its distribution with a slightly steeper slope from the head. A higher platform activity, higher publisher market concentration, better fit for weekly sales, and a more empirically accurate behavior of adoption rate appears with the inclusion of gaps larger than five weeks or simulations steps.

Results with a 36 steps gap.

Similarly with the previous increment on steps, results with a 36 gap between firms continues to accentuate the behaviors seen before. Particularly, the distribution of publisher sales and adoption behavior throughout the platforms. Adoption rates on three and fours platforms scenarios has the inflection points expected in a mixed adoption process, meaning that social influence is driving adoption as external influence does not produce that type geometrical growth. It also follows close to the empirical trend of adoption in every scenario.

Before addressing the varied behavior of platform activity, we will first show the effect

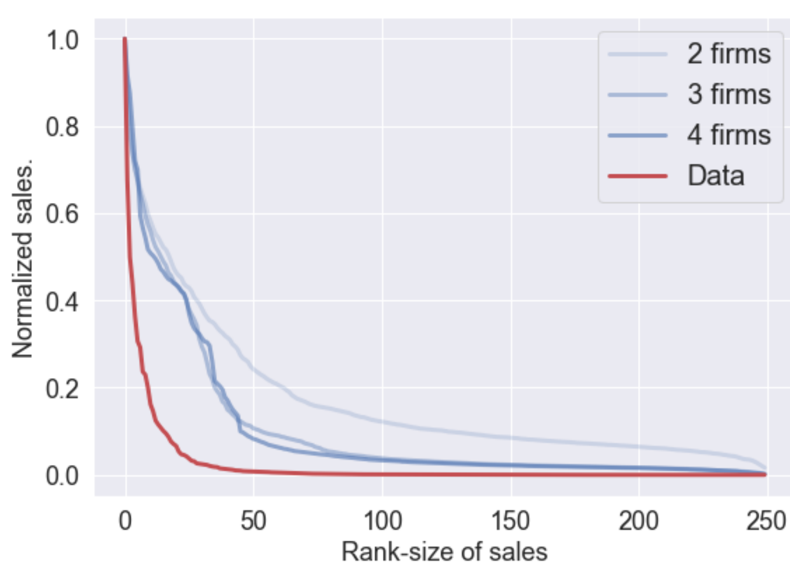

Figure 3.19: Publisher normalized unit sales.

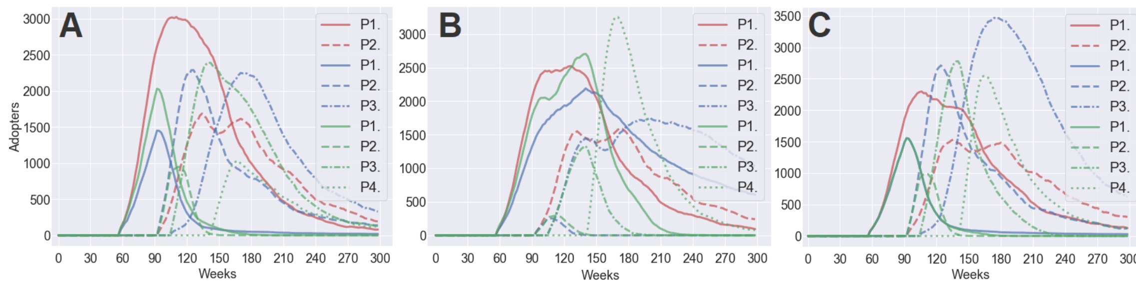

Figure 3.20: Three simulation samples of adopters in 2, 3, and 4 platforms.

that larger gaps in releases has on publisher market shares. As seen in Figure 3.19, a 36 steps gap already shifts the distribution towards narrower portions of shares for two and three platforms. Over the field of these large gaps the amount platforms also plays a role. With more platforms the distribution becomes more unequal and closer to the empirical distribution seen in the target system. This similarity clearly suggests that, at least, the process of adoption and expectation formation in the real market is slower than the modeled one. When the time-frame between platforms augments, expectation growth and softer competition open the opportunity for this type of game sales. Thus, the ratio between expectation growth and platform development are key for the formation and shaping of the experience good market.

The behavior of adopters on these runs also provides a new range of scenarios to work upon. As platforms release between longer periods of time, competition diminishes and each console is able to ignite and sustain. Although some patterns are recognizable, the spectrum of behaviors is rich and is covered superficially. General statistics of the experiments show that every scenario has some repeated particularities. First, the two platform scenario has an equal likelihood to ignite both platforms, but usually the first platform has a larger impact. This scenario also is accompanied by the least concentrated market with the highest expectation growth. On another hand, we have the three console scenario where the market is shared again. The first two platforms usually have similar shares but the later presents a less likely ignition.

Among these simulation outputs we see that platforms have higher likelihoods of behaving differently. Due to the platforms' large size and the increased duration of operations, consumers rotate among platforms and thus rates of adoption, competition, and the diffusion of game products acquire other frequencies and patterns of behavior. Figure 3.20 displays some samples of simulations with 2, 3, and 4 platform scenarios (shown in red, blue, and green respectively). Each scenario was run separately, the figures display a comparison between them. The overlapping scenarios show a varied example of the possible histories of the platform market with this release schedule. On the figure panels, the two console scenario denotes the larger impact of the first platform, as mentioned above. The other competitors follow a pattern (although not in all outputs) of growing its consumer base while the other has established for a period of steps. Other scenarios show more variability, there are cases where the earlier consoles build momentum for the later ones (C), others where platforms ignite and flop immediately or grow with stability and naturally decay (Panel C, comparison between on three and four platforms). As a closing note, it is relevant to note the capacity of portraying multiple platform market development paths. This provides an invitation to extend the model and consider an inter-generational simulation of the video game industry, portraying the market in a larger scale.

3.4.2 Multi-homing preliminary analysis.

As we know, multi-homing is one of the rich characteristics of platform competition that generate highly complex interactions between all sides within and outside of platforms. Multi-homing behavior refers to the degree on which sides are able to adopt and use more than one platform. We know that depending on multi-homing costs (including access, matchmaking, or opportunity costs), the markets business model and strategy can vary deeply. The ease of shifting between platforms makes it harder to generate exclusivity in their matchmaking operations. On the case of video game consoles, the cost of entry for consumers (i.e. buying a hardware console) has been historically high and thus multi-homing was not common for gamers. But, as games are virtually an information good that depends on the technological platform of the game console, multi-homing costs can be very low for developers depending on the hardware design and licensing policy. We now present an extension of the model that includes the capability of choosing more than one platform for both sides. With this implementation we expect to find alternate behaviors that corresponds to the empirical trends and to survey the impact of multi-homing on the systems parameters. Before any exploration on how it affects the system, we would expect that the inclusion of this behavior does nos drastically change the micro and macro behaviors of the model.

First, let us review the extended representation of multi-homing on the model. The modification affects all main agents in different ways. Consumer and developer classes are now able to select two platforms from their best interest (i.e. highest expectation and expected revenue, respectively), while platforms provide some rules of engagement. The overview for each of the agent classes and their main modifications goes as follows:

1. **Platform agent.** Although platform agents don't multi-home, they set the rules for others behavior. These rules are based on demanding a certain degree of exclusivity. So far platforms were completely exclusive (i.e. no multi-homing), now they allow any game to be released. Additionally, in section 3.4.3 we explore with limited exclusivity periods (as seen in the home console game industry), where titles are exclusive for a short period of time.

2. **Developers agent.** Developer or publisher class has the possibility of adopting one or two platforms. Once selected, the agent develops games with the specified conditions by the platform. There is no negotiation and developers are modeled as 'price takers' with a take it or leave it heuristic. Thus, once developers are accepted to enter the platform, they will continue to behave as described on the default model.

3. **Consumer agent.** As their counterpart side, consumer agents have the possibility of adopting at most two consoles. Although they may adopt more than one platform, these agents remain limited to adopt only one game per purchase. After consuming a

game, they look for another among all adopted and active platforms. After that, the rest of consumers' behavior remains the same.

Throughout the simulation, the new modifications affect mostly the behavior of developers and consumers. Platform agents provide the mentioned rules over consumers and developers, without having modifications on their behavior through the simulation. On another hand, developers' decision and production time have a major impact. Once developer agents know their best two prospects, it evaluates both and adopts them if they are good enough. When it selects them, it has to pass the conditions on license limits and accept the exclusivity requirements for the simulation. Exclusivity is modeled as time, a fix amount of steps where the developer must only produce games for one platform. The exclusivity values are given in order of adoption and developers have to release for all platforms adopted before deciding to adopt other platforms. For example, if a developer has two favourites and we have an exclusivity value of 4, it first adopts the better prospect and begins development. Then, it adopts the second one beginning development with a delay of 4 steps. This developer agent can only adopt a new platform once he releases all announced games. The simulation experiments consider exclusivity values in the range of 0, 4, 12, and 54, representing a platform with no exclusivity, a month, a quarter, and a year of exclusivity delay. Additionally, is important to remark that the model does not represent hardware architecture or any other heterogeneity that could be considered an additional cost for developers. As stated before, entry costs are exogenously given and assumed to be determined by the platform firm. Once developers have platforms, the market expectation begins to rise as consumer's attitude regarding platforms changes when developers begin releasing games. As the actual utility of game consumption is revealed to enthusiast consumers. When consumers have developed enough expectations for platforms (as with the original model), they face the possibility of selecting one or both of the top two prospects. Different from the developer class, consumer may adopt a new platform each time they evaluate platforms (i.e. when they don't currently own one) and, if they have already adopted a platform, whenever they have stopped playing the last game. This means that consumers are more flexible in multi-homing and that adoption of the platform may not correlate with game sales.

Preliminary analysis of multi-home behavior.

Developers.

The initial explorations on developer multi-homing do not reflect a significant change in behavior. Publisher firms are the only ones to multi-home their game products, as it happens in the general understanding of the 'generation wars' [Harris, 2014]. Beside the multi-homing capability, there are no additional costs or exclusivity delays. Regardless, the experiments performed with two and three platform scenarios do not show any impact. Both scenarios behave similarly without abrupt alterations to adoption rate, publisher sales, weekly sales, or consumer expectation. The active period of platforms appears to have a longer lifespan and later platforms usually are able to retain more consumers. This appears as a natural consequence of developers being able to release on the second platform as well as the first one, making the former gain advantage in developer adoption and benefiting from the developed expectations. Nevertheless, this increment on games released on platforms is not sufficient to portray a characteristic behavior of developers multi-homing on the agent-based model.

Consumers.

Results of consumer multi-homing under the model's assumptions have a clear effect on adoption. We see how platforms benefit from their promotion to consumer agents, which usually shaped the adoption of the latest to release. In the consumer multi-homing scenario, adoption on a later phase favors the first to release. While the last platform gains a faster traction, the former is able to develop its own user base via multi-homing. As there are no additional developers that contribute to this platform (given they do not multi-home on this setting), the platform falls flat along the former winner (Figure 3.21). This behavior of resisting the dominating platform through multi-homing rules also opens the range of possible scenarios through the model's simulations. The first to release has an advantage on the original batch of developers that announce games to this platform, this initial participation base appears to slightly gain over the simulation and, in the case of three platforms, being able to survive longer.

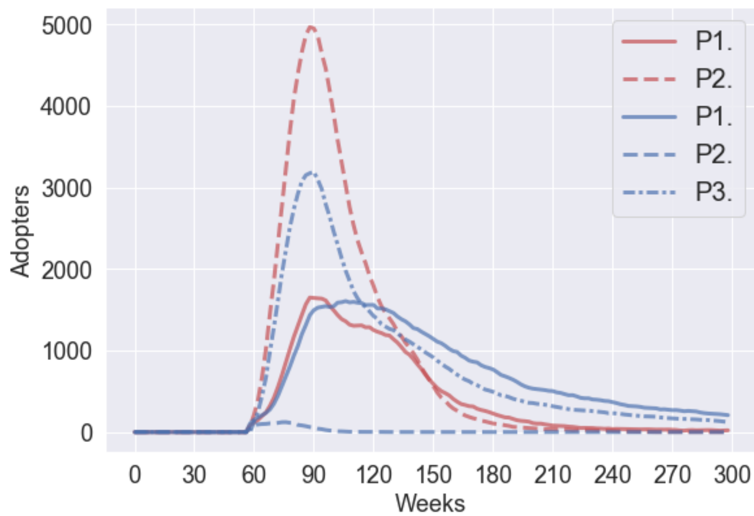

Figure 3.21: Platform adopters with consumer multi-homing.

Simultaneous multi-home behavior.

The runs on the experiment with both agents on this behavior presents the same characteristics of consumer multi-homing but with accentuated traits. Consoles that release later have a support of early consoles and quickly amass a large portion of the market (i.e. between 40% and 50%). On their counterpart, other platforms (either releasing before or after) find enough consumers that are interested; generating a competitor platform. But, alike the consumer multi-homing simulations, the interest and activity falls short for all platforms at the same time. Those consoles that release first do not see the lasting effect we saw previously. Thus, the multi-homing only contributes to the simultaneous existence of two platforms.

As we've seen so far, gaps in release dates contribute to longer platform activity. To test the effect of this longer participation we proceeded to test multi-homing behavior for both agents with a different release schedule. Figure 3.22 compares the results on simultaneous release for multi-homing in a 24 step separation console release. Although activity is widespread among all the participating platform, we do not see longer platform activity as with separated releases without multi-home. It is interesting to see that this release schedule appears to be benefited by agents selecting multiple platforms. On average, all released platforms ignite and get a high participation level. Initial inspections suggest that multi-home behavior, under the model assumptions, is detrimental to platforms when consumers engage on it. When consumer agents actively participate in more than one platform they have more options to select from, engaging with product frequently, and thus probably accelerating a loss in interest or expectation (relative to the current offers, as they have already consumed others). The inclusion of consumer multi-home behavior is questionable on its representation of the home console video game industry, as we have stated before the typical behavior would be to adopt only one platform per household.

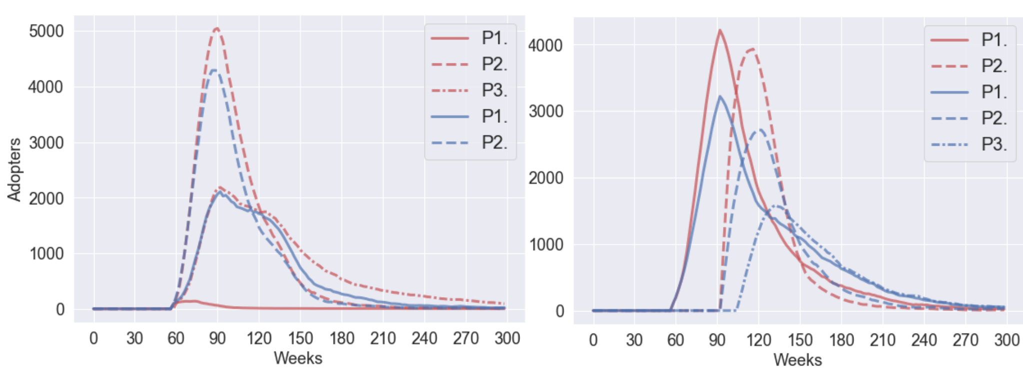

Figure 3.22: Platform adopters with simultaneous multi-homing.

3.4.3 Platform strategies: license exclusivity and price structure.

Finally, we go over the simulation experiments related to the platform firm's management over side's participation. Meaning, the particular decisions and platform design that attempt to present an overall growth by delivering incentives and disincentives when needed.

Effect of license exclusivity on multi-homing adoption.

For developer agents we performed an experiment including different levels of temporal exclusivity. This entailed that any developer that releases a game for a platform would have to wait a certain amount of simulation steps before releasing a game on another platform. This limitation represents the capability of making a developer and game exclusive to a single platform based on either the development operation (common on early generations where hardware and operative systems were widely diverse) or part of the actual contract. Opposite to what we expected, the exclusivity bans had little to no impact on the market macro behaviors that we are interested on. The most noticeable effect is the reduction of average expectation in total. Based on the simulation output, a market with a larger exclusivity limit for developers makes consumer agents to develop their expectation slower than with shorter ban duration.

Effects of cost.

To understand the effects of cost within the model we tested changes on the included parameter of adoption cost. As stated in chapter 2, the adoption threshold plays the role of cost in terms of the requirement needed to consider adoption a positive payoff. There are no prices or any similar mechanism beyond this adoption threshold, which so far has been given to agents exogenously. Changes related to this arbitrary adoption requirement are a direct modification on the likelihood of adoption. Thus, we do not model price for consumers or any other particular internal behavior related to this; we basically adjust the probability of adoption for consumers. Within this frame, we established a high and low cost for consumers. Similarly, the evaluation on publisher agents was modified regarding the evaluation of potential platforms. Equation 2.15 is modified with a positive or negative value to address the incentive or additional cost for any particular platform. Values for the upper and lower limit of publisher agents were picked by surveying the distribution of the τ values of equation 2.15. Thus, we find that publishers usually evaluate a relative benefit between 0.01 and 0.02 when adopting a competitive platform. Thus, we set a high cost for this agent at 0.02. On the lower limit (i.e. in the case that the platform wants to provide incentives for developer participation), developers are given a cost of -0.01, which would tip the adoption of that particular platform. On the other side of the platform, consumer agents regularly evaluate the benefit of a particular platform between 0.25 and 0.75. Consequently the consumer agent limits of costs are set on 0.75 for high side, and 0 for the lower value (remember that consumers have so far incurred in an adoption cost or threshold of 0.5).

An initial set of simulations with the mentioned settings do not show significant differences, as expected. As firms used the same costs the behavior does show a preference for any platform, but also it does not alter the macro behaviors we've seen so far. A second set of experiments revised the same conditions with a 24 release gap schedule. Results from the second attempts reveal some effects of costs on the long run on adoption and the market distribution of publisher sales.

Experiments with high costs for developers show an important alteration on the macro

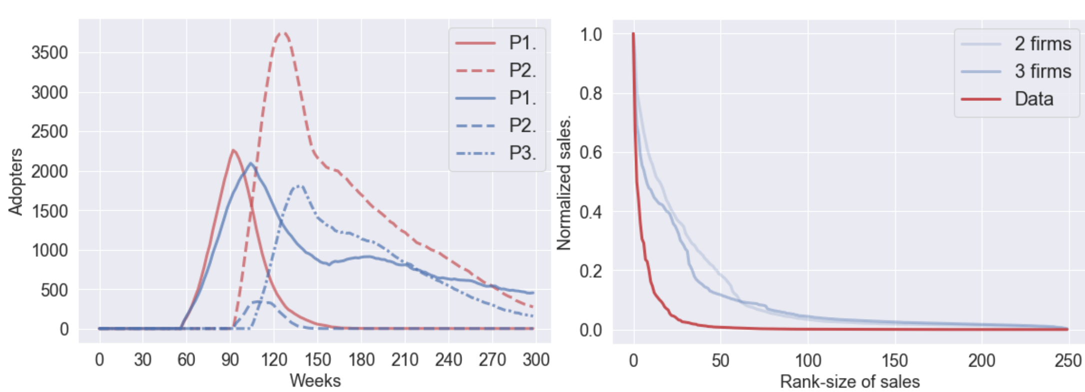

Figure 3.23: Developers with high cost: Adopters and Publisher sales.

behavior of the model. Platform activity displays a change on the longevity of platforms (Figure 3.23). Consoles releasing at different steps are able to ignite and sustain an operation throughout the whole life-cycle of the market. The adoption process sees the typical growth but decay behaves differently, decreasing at the usual speed at first to recede and slowly decrease later on. On the other hand, publisher sales also sees a prominent reshape. The distribution of game sales for scenarios with two and three platforms has a better fit to the empirical trend than most simulation initialization parameters. This change in adoption and sales behavior is a natural consequence of most developer agents rejecting a second or even a first platform adoption. The left over developers would then seek for new opportunities and if the prospect platform grows in value, then the agent will adopt. This period of latency (which could also be expected in real markets) shapes the behaviors seen in Figure 3.23. As developers have a delayed entry into platforms, consumer agents receive new games at a slower pace; which also affects the speed of consumption and loss of interest. This ultimately provides platform with the possibility of engaging both sides for a longer period. On some cases, as depicted on the figure, the effect is not only for the first to release console. The same behavior would affect the amount of releases, as they would be offered to the market in a wider time-frame. This lower density of products allows the social influence and hype behavior to select from fewer games.

We now proceed to test the effect of the 'price schedule' prototype; meaning, the inclusion of incentives for side's participation. Simulations include the same cost boundaries, but this time they are only applied to the first console (providing a contrast between platforms). Furthermore, the experiments also considers incentives. A broad contrast between typical behaviors with high costs over an incentive package is shown in Figure 3.24. In both scenarios, incentives or lower costs do not generate an incentive towards adopting the first platform. On the contrary, high costs simulations (shown in blue) have a clear pattern on being the second platform to gain traction and dominate the market (an expected consequence of relatively higher prices on the competitor). When we include incentives the tipping over to the second platform is not common but appears as seen on Figure 3.24 for two and third platforms scenarios (A and C respectively). Another interesting behavior depicted in the same figure is the distribution of games sales. The manipulation of entry prices that generates an advantage to one platform not only affects the development of a significantly larger platform, it also modifies the game software market. When a platform achieves dominance that persists over time, the effect is clear over publishers sale distribution (Figure 3.24, panel B and D for two and three platforms respectively). We've seen this behavior on previous simulation outputs. The extent of this effect even presents, on some runs, a larger concentration than the empirical evidence. Once again the model behaves as expected regarding the inclusion of an incentive for developers. We see how an incentive biases the game sales distribution significantly more than the high costs outcomes. This results show that dominance alone is not enough, and that if this is created by catering to large audiences, the internal market of the winner platform could find highly unequal

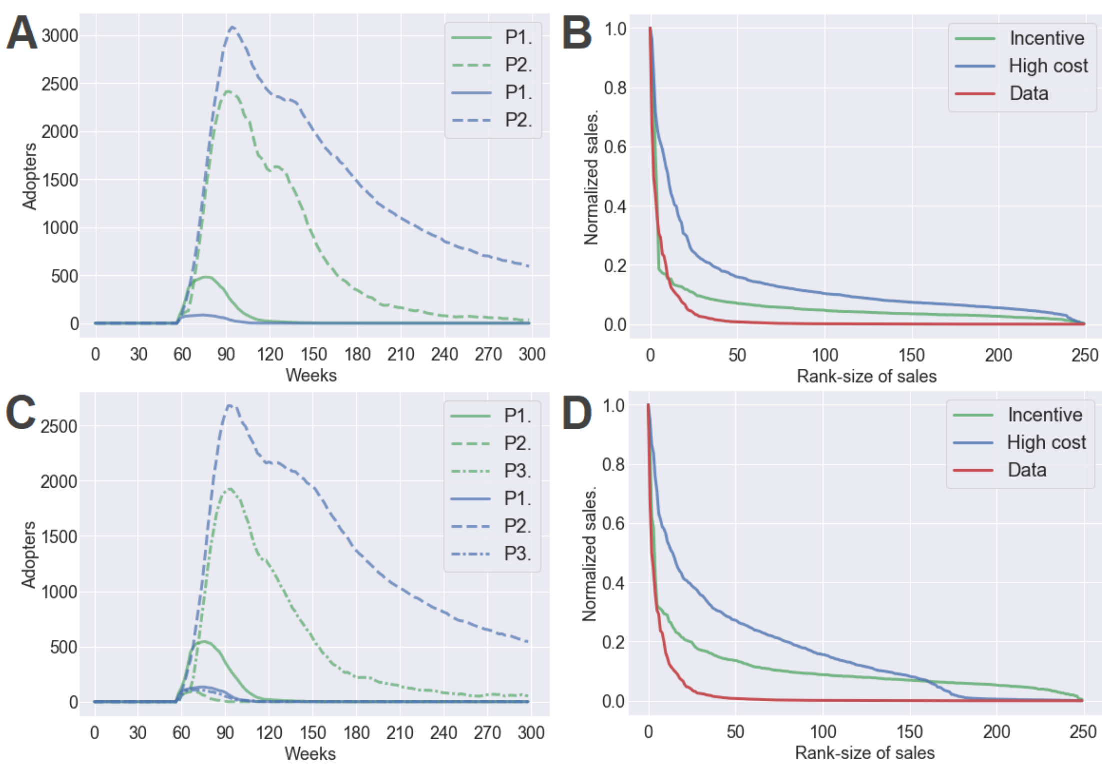

Figure 3.24: Comparison between high cost and participation incentive.

distributions of market share.

3.4.4 Insights on Extension 3.

Generally speaking, the simulations presented have shown the range of assumptions that could be implemented, being either attributes or behaviors of the target system. The last section opens a new framework to study platform markets and its multi-home behavior. The inclusion of different entry times for releases provides a wider range of possibilities for modeling this type of markets. The simple inclusion of specific traits allowed the survey of the markets' possible scenarios. For example, acknowledging the capacity of actors on each side selecting multiple platforms raises new questions about the speed of adoption and the relevance of modeling the appropriate expectation growth rates within the market; regardless of the representation or technique used to do so. Finally, as we review basic elements of platform strategy, the results qualitatively fit the expected behaviors; setting a new scenario framework to address specific questions.

The exploration of incentives provided more results regarding the relation between platform dominance and game developer sales concentration. Within the model, as more participants a platform is able to amass, the probability of generating blockbusters among the consumer base is higher. In other words, as the market is less divided, the effects of more consumers in peer-recommendation network produce more events that favor a handful of publishers.

3.5 Conclusion.

Throughout the three extensions we've revised several aspects that would be of interest to understand the theory, operations, and ultimately strategical aspects of entertainment platform markets. The first extension displayed the different outcomes of defining consumer and product types with particular attribute values, and assessing the macro behavioral differences when they appear. Simulations with these type of experiments brought light to the issue of market diversity on the consumer side and the design experience goods. Ultimately, it also contributed to propose experiments where markets had targeted consumer segments with corresponding product features. Which, if developed in a further extent, can frame the computational study of quality in experience goods markets. Additionally, the role of platform properties was also studied. A second extension provided experiments on consumer perception. Although there are many behaviors and cognitive processes to be included, one of the basic elements for the purpose of an experience market model is the ability to detect the product features. Thus, the model output suggests that perception, alike attributes heterogeneity, is also a double-edged sword depending on the market conditions. Finally, a revision to aspects that are relevant to platform management was presented. Experiments that included diverse release schedules, manufacturer's enforcement of licence agreements (i.e. exclusivity deals), and a basic representation of a price structure.

On a different note, there is an interesting case for diversity on these general surveys. As with other simulations on the development of these extensions, there appears to be an middle sweet spot for features diversity, strongly suggesting that the effect of feature heterogeneity is non-linear. In the simple model of consumer cognition, this happens as we know the share of different feature vectors and the percentages or segments of consumer population they will satisfy. Still, the phenomena seen in the simulation can be generalized to the target system and other markets with experience or cultural products. In the simulation's simple terms, as similarity increases products limit their potential target consumers, and as it decreases the market may get unstable and even lack platform ignitions. In terms of marketing and experimental psychologists, the difference between a platform that achieves a 'just noticeable difference' may have a major impact in a highly similar market.

The experiments presented propose new ways to address how we model these platform systems, and what are the behavioral implications of its assumptions, rules, and limitations. The three extensions took a different aspect to pursue elemental questions over this type of market. Although the model does not intent to be used as a decision making support tool of a real platform market, it signals the consequent behavior that necessarily emerges from any definable model. The work presented here is a theoretical exercise of describing and modeling to understand the complex relationships between actors in the home console market, particularly focused on its multi-sided structure and the presence of products with cultural or experience good traits. Future work should consider the collection of more empirical data to calibrate aspects like an estimate of consumer attitudes, multi-homing numbers for developers and consumes, average individual activity on platforms, and more details on developer statistics. If the availability to data exists, an ideal target system would be the mobile game market. Furthermore, the model can be generalized to many types of industries, particularly including content platforms like YouTube, Spotify, or Netflix. Considering the impact they have gained in the entertainment market and popular culture, it would be of great relevance to analyze the unintended consequences of a market with high uncertainty.

A final conclusion on the development of this type of theoretical tool refers to the future design and implementation of agent-based models. The mere design of an agent based model falls short if it is the purpose or objective is not clear. A theoretical revision with empirical calibration is even epistemologically different to developing concrete and reliable models of operational or pragmatic uses. The agent-based model presented here has been calibrated with available data for purposes of external validation, while typical behaviors on the model theoretical foundations are also used for internal validation. Considering the wide spectrum of questions, scenarios, and model testing seen so far, the agent-based framework of the video game industry achieves its purpose to describe its general behavior; while providing new information about the implications of how we think the entertainment platform markets behaves.

Appendix A: Python code of the agent-based model.

The files for the agent-based model are hosted on Github/AndreLhu as CSS GMU Doctoral Dissertation. Otherwise, please contact the author to receive the Python code and references to documentation.

A.1 Main python code

This section covers the main functions used to initialize the simulation by calling the agent objects (detailed on the following sections) with the specified parameters. Along the functions used to begin the simulation by an instance of the Market object, there are many other functions that assist on saving the simulation data and delivering brief statistical reports when several simulations are executed. Secondary functions that include plotting, network formation and display, or the use of CUDA for better a performance of numerical operations that are not essential for the model's operation are not included in the appendix.

```
{\singlespacing
#!/usr/bin/python2.4
# -*- coding: utf-8 -*-

import numpy as np
import random as rd
import matplotlib.pyplot as plt
import matplotlib as mpl
mpl.rc('savefig',dpi=100)
import winsound
import time
import networkx as nx
import seaborn as sns
```

```
import pandas as pd
from numba import autojit
from collections import Counter
from matplotlib import animation
import theMarket
from theCases import *

Basic_Test = {'name': 'Test', 'plats': 2, 'devs' : 250,
              'cons' : 2000, 'step' : 300, 'gens' : 1,
              'dates': [55,56,57,58], 'all'  : True, 'soc'  : 0.3,
              'media': 0.7, 'bound': 1, 'pref_n': 2, 'feat_n': 2}

#Main functions
def __main__(case,experiments,exp_plot,plot_all=True,preferences='uniform',
             features='uniform'):
    plats,devs,cons = case['plats'],case['devs'],case['cons']
    step,exper,socinf  = case['step'],case['name'],case['soc']
    massinf,devinf = case['media'],case['bound']
    pref_n,feat_n = case['pref_n'],case['feat_n']
    t0,start_at,preftag = time.time(),0,None
    target_par = ['cum_avg','cum_med','plat_rank','dev_rank','releases',
                  'dev_plats','expect']
    experiment_d = {i:[] for i in target_par}
    for i in range(experiments):
            try:
                experiment = []
                print '\n Running experiment # '+str(i+1)
                sim,plt_res = run_sim(plats,devs,cons,
```

```
        netd='random',
        dev_bnd=devinf,
        generations=1,
        release_dates=case['dates'],
        socinf=socinf,
        price=[1]*plats,
        quality=[1]*plats,
        steps=step,
        plot=True,
        name=exper,
        massinf=massinf,
        plot_allb=plot_all,
        preferences=preferences,
        features=features,
        pref_n=pref_n,
        feat_n=feat_n)
rank,targeted,temporal,temp2 = [],[],[],[]
n_targeted = range(125)

for j in sim.devs:
    rank.append(sum(j.unit_games.values()))
    if int(j.ID) in n_targeted:
        targeted.append(sum(j.unit_games.values()))
rank.sort(reverse=True)
targeted = [targeted[iii]+float(iii)/1000 for iii in \
            range(len(targeted))]
t_taken = []
for k in range(len(rank)):
```

```
                    token = False
                    for target in targeted:
                        if target >= rank[k] and target not in t_taken:
                            t_taken.append(target)
                            temporal.append(k+1)
                            token = True
                            break
                    if token == False:
                        temp2.append(k+1)
                sim = experiment_info(sim,step,temporal,temp2)
                experiment.append({i:sim.experiment})
                dfexp = pd.Series(experiment)
                dfexp.to_pickle('Simulations/Exp'+str(exper)+'_'+\
                    str(start_at+i+1))
                for pl in plt_res.keys():
                    experiment_d[pl].append(plt_res[pl])
            except Exception as e:
                print 'Error in sim #'+str(i+1)+' : '+str(e)

    if exp_plot:
        plot_experiment(experiment_d,devs)
    get_alert()
    return dfexp,temporal #former "sim"

def G(case=Basic_Test,info=False,experiments=1,exp_plot=True,plot_all=False,
      preferences='uniform'):
    if info:
        print '\nRunning case: "'+str(case['name'])+'".\n'
```

```
        print 'Consumers: '+str(case['cons'])
        print 'Publishers: '+str(case['devs'])
        print 'Platforms: '+str(case['plats'])
        print 'Peer factor at: '+str(case['soc'])
        print 'Media factor at: '+str(case['media'])
        print 'Repeat '+str(experiments)+' times for experiments.'

    sim,temp = __main__(case,experiments,exp_plot,preferences=preferences,
                        features='uniform')
    return sim,temp

@autojit
def create_pref(population):
    cons,netlinks,agents = range(0,population),0,[]
    for me in cons:
            neighborhood = []
            for node in cons:
                fThresh = float(1.0)/float((netlinks+1)* \
                    (len(neighborhood)+1))
                if(rd.random() <= fThresh):
                    if me != node:
                        neighborhood.append(node)
                        netlinks += 1
            agents.append(neighborhood)
    return agents

@autojit
def create_rand(population):
```

```
    cons,netlinks,agents = range(0,population),0,[]
    for me in cons:
            p = 0.005
            neighborhood = []
            for node in cons:
                if rd.random() < p:
                    neighborhood.append(node)
                    netlinks += 1
            agents.append(neighborhood)
    return agents

#III - Run_sim() actual simulation of N steps according to parameters.
def run_sim(p,d,c,price,quality,steps=300,netd='random',mkttime=100,
    plot=True,dev_bnd=1,generations=1,release_dates=None,socinf=0.1,
    massinf=1,name='Normal run',plot_allb=True,preferences='uniform',
    features='uniform',pref_n=2,feat_n=2):
    global market
        t0 = time.time()
    netdd = create_pref(c)

    market = theMarket.Market(p,d,c,price,netdd,mkttime,dev_bnd,
        generations, quality,steps,release_dates,socinf=socinf,
        massinf=massinf,preferences=preferences,
        features=features,pref_n=pref_n,feat_n=feat_n)
    market.init_agents(market)
    market.pos_to_ID(market)
    t1 = time.time()
    print 'Init done in T: '+str(t1-t0)+' secs.'
```

```python
    for s in range(steps):
        market.step(market)
    t2 = time.time()
    if plot_allb == True:
        results = plot_all(market,steps,d)
    else:
        results = False
    return market,results

#Functions for simulation data, visualization, and analysis:
def get_empirics(plot=False):
    par1df = pd.read_pickle('Empirics/Empirics_Parameter1')
    par2df = pd.read_pickle('Empirics/Empirics_Parameter2')
    par3df = pd.read_pickle('Empirics/Empirics_Parameter3')
    par4df = pd.read_pickle('Empirics/Empirics_Parameter4')

    if plot:
        total_platforms = list(par1df.Distro_gen)[-1]
        plt.title('Average sale distribution (platform).')
        plt.bar(np.arange(0,len(total_platforms)), \
        total_platforms,width=1)
        plt.show()
        plt.title('Average adoption (cumulative).')
        for k in ['AVG','STD','MED']:
            plt.plot(par2df[k],label=k)
        plt.legend()
        plt.show()
    return par1df,par2df,par3df,par4df
```

```
#Get main data from each simulation run.
def experiment_info(market,steps,temporal,temp2):
    for pl in market.announced_plat:
        mkt_rec = market.record[str(pl)]
        temp_record=[0]*(steps-len(mkt_rec))+mkt_rec
        market.experiment['adopters'][pl] = temp_record
        dev_rec = market.dev_rec[str(pl)]
        temp_dev_rec=[0]*(steps-len(dev_rec))+dev_rec
        market.experiment['developers'][pl] = temp_dev_rec

    for pl in market.plats:
        #Get Cumulative adoption (consumer).
        max_hw = max(pl.hwsales)+0.01
        csales = [float(plp)/max_hw for plp in pl.hwsales if \
        float(plp)/max_hw != 1 and float(plp)/max_hw != 0]
        ccsales = [sum(csales[(i-1)*(len(csales)/20):i* \
        (len(csales)/20)]) for i in range(1,21)]
        max_ccsales = max(ccsales)+0.01
        market.experiment['cumulative'][pl] = [0]+ \
        [float(cc)/max_ccsales for cc in ccsales]

    #Get Totals via Weekly
    market = central_weekly(market,experiment=True)

    a = [sum(i.unit_post10weeks.values()) for i in market.devs]
    a.sort(reverse=True)
    market.experiment['dev_rank'] = a
```

```
rel_games = []
for pl in market.plats:
    rel_games.append(len(pl.games))
rel_games.sort(reverse=True)
market.experiment['releases'] = rel_games

mean,stdev = get_weekly_games()
market.experiment['weekly_mean'] = mean
market.experiment['weekly_std'] = stdev

market.experiment['targetrank'] = [temporal,temp2]
sample = rd.sample(market.cons,int(len(market.cons)/10))
node , target , product = [] , [], {}
for c in sample: #sampled consumer
    if len(c.old_plat) >=1:
        product[c.ID] = c.old_plat[-1]
    else:
        product[c.ID] = 'None'
    for n in c.neighbors:
        node.append(c.ID)      #get his links
        target.append(n)
        for e in market.cons:
            if e.ID == n:
                if len(e.old_plat) >=1:
                    product[e.ID] = e.old_plat[-1]
                else:
                    product[e.ID] = 'None'
```

```
                    for nn in e.neighbors:
                        node.append(n)
                        target.append(nn)
                        for nnn in market.cons:
                            if nnn.ID == nn:
                                if len(nnn.old_plat) >=1:
                                    product[nnn.ID] = nnn.old_plat[-1]
                                else:
                                    product[nnn.ID] = 'None'
    market.experiment['network'] = [node,target,product]
    return market
```

A.2 Market class.

```
class Market(object):
    def __init__(s,platq,devq,consq,price,netd,time,devbound,releases,
        quality,tot_step,release_dates=None,socinf=0.1,massinf=1,
        preferences='uniform',features='uniform',
        console_features='uniform',pref_n=2,feat_n=2):

#v3.0 : Chapter 3 : Preference and Feature definition, multihoming
        s.exclusivity = [0,0]
        perception = 3
        print 'Consumer perception : '+str(perception)
        print 'Targeted developers : '+str(devq/2)
        #Uniforms
        preferences = 'uniform'
        features = 'uniform'
        console_features = 'uniform'
```

```
#Example of definition of vector types, preferences, and features.
#typeA = [1,1,1,1,1,-1,-1,-1,-1,-1]
#typeB = [-1,-1,-1,-1,-1,1,1,1,1,1]
#preferences = [typeA]*(consq/2) + [typeB]*(consq/2)
#features = [[iii*(pref_n-2) for iii in typeA]] * (devq)
#features = [typeA] * (devq)
#console_features = [[iii*(pref_n-2) for iii in typeA]] * (platq)

typeA = [1]*10
preferences = [typeA] * (consq)
typeB = [1,-1,1,-1,1,-1,1,-1,1,-1]
features = [typeB] * (devq)

#v3.0 : Chapter 3 - Features
#Get iterables
prices = iter(price)
if release_dates == None:
    release_dates = iter([None for i in range(platq)])
else:
    release_dates = iter(release_dates)

#First initiate platforms
if console_features == 'uniform':
    s.manuf = [thePrincipal.thePrincipal(i,prices.next(),time,
        releases,features='uniform',release_time= \
        release_dates.next(),
        massinf=massinf) for i in range(platq)]
```

```
else:
    console_features = iter(console_features)
    s.manuf = [thePrincipal.thePrincipal(i,prices.next(),time,
            releases,
            features=console_features.next(),
            release_time=release_dates.next(),
            massinf=massinf) for i in range(platq)]
if features == 'uniform':
    s.devs = [theDev.theDev(i,devbound,massinf=massinf,
            feat_type=features,feat_n=feat_n) for i in range(devq)]
else:
    s.devs = [theDev.theDev(i,devbound,massinf=massinf,
                    feat_type=features[i]) for i in range(devq)]
s.licensed = [dev.ID for dev in s.devs]#[:10]
s.netlinks = 0

#v3.0 : Chapter 3 - Preference
if preferences == 'uniform':
    s.cons = [theCons.theCons(i,netd,socinf,preference=preferences,
        pref_n=pref_n,perception=perception) for i in range(consq)]
else:
    s.cons = [theCons.theCons(i,netd,socinf,preference= \
    preferences[i],
        perception=perception) for i in range(consq)]
s.steps,s.tot_step,s.maxtech = 0,tot_step,1
s.plats,s.plat_features,s.games,s.games_features = [],{},{},{}
s.pos_ID = {}
```

```python
    #Keep track of Main Behaviors
    s.experiment = {'adopters':{},'cumulative':{},'developers':{},
                    'totals':{},'expectatives':{},'dev_rank':{},
                    'weekly_mean':[],'weekly_std':[]}
    s.announced_plat,s.released_plat,s.retired_plat,s.names= \
        [],[],[],[]
    s.record = {str(i):[0] for i in range(platq)}
    s.plat_adopter = {str(i):[0] for i in range(platq)}
    s.dev_rec = {str(i):[1] for i in range(platq)}
    s.expec_rec = {str(i):[1] for i in range(platq)}
    s.expec_rec['M'] = [0]
    s.expec_rec['M_SD'] = [0]
    s.dev_multihome,s.dev_mh_std,s.dev_plats,s.cm_rec = [0],[0],[0],[0]

    #Debugging
    s.debug_expect = {i:{} for i in range(45,65)}
    s.disadoptersnet = 0
    s.disadoptersall = []

def init_agents(s,market):
    [cons.init_me(market) for cons in s.cons]

def pos_to_ID(s,market):
    temp_ = {s.cons[i].ID: i for i in range(len(s.cons))}
    s.pos_ID = temp_

#@autojit
def step(s,mkt):
```

```
    activate = rd.sample(s.cons,int(float(len(s.cons))*0.5))
    if s.steps % 2 == 0:
        s.keep_track(mkt)
    for cons in activate:
        cons.step(mkt)
    for cons in activate:
        cons.update(mkt)

    [manf.step(mkt) for manf in s.manuf]
    total_mkt_power = sum([sum([v for v in \
        d.unit_games.values()]) for d in s.devs])
    for dev in s.devs:
        dev.mkt_power = float(sum([v for v in \
                    dev.unit_games.values()]))/(total_mkt_power+0.01)
    [devs.step(mkt) for devs in s.devs]
    [plat.step(mkt) for plat in s.plats]
    s.steps += 1

def keep_track(s,market):     #Record adoption, devs and expectations
    s.pos_to_ID(market)
    tech = 1 #[manuf.release_d[0] for manuf in s.manuf]
    s.maxtech = 1 #max(tech)
    tp1,tp2,tp3,tp4=[],[],[],[]
    #Consumer loop
    for plat in s.plats:
        tp1,tp2,tp3,tp4=[],[],[],[]
        for c in s.cons:
            tp1.append(c.adopt['plat'][str(plat.ID)])
```

```
            tp2.append(c.expect['plat'][str(plat.ID)])
            tp3.append(c.expect_m)
            if c.consumeme == True:
                tp4.append(1)
    #Keep records of:
        s.expec_rec[str(plat.ID)].append(np.median(tp2)) #Mean expect
        s.record[str(plat.ID)].append(sum(tp1)) #Total adopters
        #Total developer/publisher adopters
        s.dev_rec[str(plat.ID)].append(len(set([d for d in plat.devs])))
        s.expec_rec['M'].append(np.mean(tp3)) #Mean expectative
        s.expec_rec['M_SD'].append(np.std(tp3))
        s.cm_rec.append(sum(tp4))

    #Dev loop
    tp1,tp2 = [],[]
    for dev in s.devs:
        tp1.append(len(dev.plats))
        if dev.plats != []:
            tp2.append(1)
    s.dev_multihome.append(np.average(tp1))
    s.dev_mh_std.append(np.std(tp1))
    s.dev_plats.append(len(tp2))
```

A.3 Consumer class.

```
@numba.jit(nopython=True)
def numba_interact2(npg,self_inf,self_expect):
    val = self_expect
    for n in npg:
```

```
            val = val + n*self_inf
        return float(val)/float(len(npg)+1)


class theCons(object):
    def __init__(s,ID,netd,socialinfluence,Thresh_type='general',S=3,Q=10,
                 T=0.6,preference='uniform',pref_n=2,perception=0):
        s.ID          = ID

        #Expectations
        s.expect,s.old_expect = {},{}
        s.perception = rd.sample([0,1,2,3,4,5,6,7,8,9],perception)

        #Preferences
        if preference == 'uniform':
            s.preferences = [1]*pref_n+[rd.uniform(-1,1) for i in \
                range(Q-pref_n)]  #5D (Q=5) vector preferences \
        else:
            s.preferences = preference

        #Consumer habits and states
        s.consume_rate  = 2            #Fixed product use (80-120)
        s.consumed = s.consume_rate
        s.prospect = None
        s.playing = False

        #Purchase trigger
        if Thresh_type == 'general':      s.thresh  = T
        elif Thresh_type == 'individual': s.thresh  = rd.uniform(0,1)
```

```
        #Demography + Soc.Net.
        s.wealth = rd.random()       #Uniform wealth (0-1). Placeholder
        s.influence = socialinfluence
        s.neighbors   = []
        s.position    = [0,0]

        #Given network
        s.netd = netd  #Agent social network degrees, circle of influence

        #Purchases
        s.manuf,s.games = None,[] #No target plat, no o

        #Ver 3.0, plats are now a list for multi homing
        max_multihoming = 1
        s.plat = [None] * max_multihoming

        #Memory
        s.mem_plat,s.mem_dev,s.old_plat = {},{},[]
        s.old_manuf,s.consumeme = None,False
        s.store = {} #Used for simultaneous update of expectations

        #Record keeping
        s.plat_steps = []

#External functions (Called by Market()):
#I - Set variables according to market (platforms and consumer population).
    def init_me(s,market):
```

```
        #Mean Expectation
        s.expect_m = 0

        #Expectation by platform / extendable for Expectation by Game.
        s.expect = {'plat':{str(i):0 for i in \
                            range(len(market.plats))},'game':{}}
        s.old_expect = {'plat':{str(i):0 for i in \
                                range(len(market.plats))},'game':{}}

        #Adopt by platform / (Games(?))
        s.adopt = {'plat':{str(i):0 for i in \
                           range(len(market.plats))},'game':{}}

        #Experience by platform / (Games(?))
        s.experience = {'plat':{str(i):0 for i in \
                            range(len(market.plats))},'game':{}}

        #Purchase and temp expect
        s.bought = {'plat':{str(i):False for i in \
                            range(len(market.plats))},'game':{}}
        s.store  = {'plat':{str(i):0 for i in \
                            range(len(market.plats))},'game':{}}

#Network: Build list with surrounding neighbors - Erdos-Renyi.
        #CUDA
        #s.gpu_sub_interact2 = cuda.jit(device=True)(s.sub_interact2)
        if type(s.netd) == list:
            s.neighbors = s.netd[s.ID]
```

```
        elif s.netd == 'preferential':
            for node in market.cons:
                if node.ID != s.ID:
                    fThresh = float(1.0)/float((market.netlinks+1) \
                                    *(len(node.neighbors)+1))
                    if(rd.random() <= fThresh):
                        node.neighbors.append(s.ID)
                        market.netlinks += 1
        elif s.netd == 'random':
            for node in market.cons:
                p = 0.01
                if rd.random() < p:
                    node.neighbors.append(s.ID)
                    market.netlinks += 1

#II - Update s.expect according to temporal expect (s.store).
    def update(s,market):
        for p in market.announced_plat:
            if s.bought['plat'][p] == False:
                s.expect['plat'][p] = s.store['plat'][p]
            else:
                s.expect['plat'][p] = s.experience['plat'][p]
        #Update general expectative towards products (s.expect_m) -
        if len(market.announced_plat) > 0:
            s.expect_m = np.mean([float(s.expect['plat'][str(p)]) for p in\
                                  market.announced_plat])
        for game in s.store['game'].keys():
            if game in s.games:
```

```
                s.expect['game'][game] = s.experience['game'][game]
            else:
                s.expect['game'][game] = s.store['game'][game]

 #III - Main step function for every time-tick.
    #@numba.jit(nopython=True) #@autojit
    def step(s,market):
#0. Interact with others
#Activation of interaction. Be influenced by others.
        s.interact(market)
        s.plat_steps.append(s.plat)

        #2. Adopter behavior: search and consume games (Adopter).
        #Main step changed for Multi Homing extension on Chapter 3.
        #Check Ver 2.0 for older consumer behaviors
        ix = -1
        for splat in s.plat:
            ix += 1                   #Index
            if splat != None:
                s.consumed -= 1
                #Not playing?
                if s.playing == False:
                    #Want to play more games? Get games in my platform
                    for ps in market.plats:
                        if ps.ID == splat:
                            games_in_plat = ps.games.keys()
                    if np.mean([s.expect['game'][g] for g in  \
                        games_in_plat if g not in s.games]) < 0:
```

```
            s.adopt['plat'][splat] = 0
            s.old_plat.append(splat)
            s.old_manuf = str(splat)[0]
            for platform in market.plats:
                if platform.ID == splat:
                    platform.users -= 1
                    break
            s.plat[ix],s.consumeme,s.playing = None,False,False
        elif rd.random() < s.wealth:
            s.choose_game_to_buy(market)

    #50% chance of stop playing.
    if s.playing and rd.random() < 0.5:
        s.playing = False

    #If already consumed then leave platform adoption
    if s.consumed <= 0:
        s.adopt['plat'][splat] = 0
        s.old_plat.append(splat)
        s.old_manuf = str(splat)[0]
        for platform in market.plats:
            if platform.ID == splat:
                platform.users -= 1
                break
        s.prospect = None
        s.plat[ix],s.consumeme = None,False
        s.playing = False
```

```
            #3. Evaluate otherwise (Non Adopter).
            elif splat == None:
#If median expectation is high enough, search platforms (prospect) to adopt.
                if rd.random() < s.expect_m and  \
                len(market.released_plat) > 0:
                    s.compare_plat(market)
                #Have a prospect? Try to buy it!
                if s.prospect != None:
                    s.go_buy(ix,market)

            elif type(splat) not in [None,str]:
                print type(splat)

#Internal functions (called by self to process interaction + evaluation)
    #I - Interact with others and change expectation (s.expect)
    #@autojit
    def interact(s,market):
        #Go through non-purchased plats and update expectations,
        marketpos = market.pos_ID
        for p in market.announced_plat:
            s.sub_interact1(market,marketpos,p)
        non_played_games = [k for k,v in s.expect['game'].items()  \
            if k[:3] not in s.old_plat and s.experience['game'][k]  \
                == 0][:10]
        if len(non_played_games) > 0 and numba_mode == False:
            s.store = s.sub_interact2(market.cons,marketpos, \
            non_played_games)
        elif numba_mode == True:
```

```
        game_val = []
        for g in non_played_games:
            game_val.append([float(market.cons[n].expect['game'][g]) \
            for n in s.neighbors])
        for g in range(len(non_played_games)):
            s.store['game'][non_played_games[g]] = \
            numba_interact2(game_val[g],s.influence,
                                s.expect['game'][non_played_games[g]])

#@autojit
def sub_interact1(s,market,marketpos,p):
    if s.bought['plat'][p] == False:   #Get expect from neighbors
        others_expectatives = \
        [market.cons[int(marketpos[id_])].expect['plat'][p]* \
            s.influence for id_ in s.neighbors] #Expect from neighbors
        tot = 0
        for e in others_expectatives:
            tot = tot + e
        tot = tot + s.expect['plat'][p]
        s.store['plat'][p]=float(tot)/float(len(others_expectatives)+1)

        if market.steps in range(45,65):
            market.debug_expect[market.steps][s.ID]= \
                [s.expect['plat'][p],others_expectatives,
                s.store['plat'][p]]

def sub_interact2(s,marketcons,marketpos,non_played_games):
    for gamename in non_played_games:
```

```
        tot = 0
        for n in s.neighbors:
            tot = tot + marketcons[n].expect['game'][gamename] \
            *s.influence
        tot = tot + s.expect['game'][gamename]
        s.store['game'][str(gamename)] = float(tot)/ \
        float(len(s.neighbors)+1)
    return s.store

def post_evaluation(s,product_features):
    normalized_feat = product_features/np.linalg.norm(product_features)
    normalized_pref = s.preferences/np.linalg.norm(s.preferences)
    return np.dot(normalized_feat,normalized_pref)

def perceive(s,game_value):
    if len(s.perception) > 1:
        perceived_features = [game_value[i] for i in \
                        range(len(game_value)) if i in s.perception]
        relevant_preferences = [s.preferences[i] for i in \
                        range(len(s.preferences)) if i in s.perception]
        normalized_feat = perceived_features / \
            np.linalg.norm(perceived_features)
        normalized_pref = relevant_preferences / \
            np.linalg.norm(relevant_preferences)
        utility = np.dot(normalized_feat,normalized_pref)
        return utility
    else:
        return 'boop'
```

```
#II - Experience a platform (via demo or purchase).
def experience_plat(s,market,ix,target_plat):
    plat_features = market.plat_features[target_plat] #Get features
    exp = s.post_evaluation(plat_features) #Normalized Dot Product
    s.experience['plat'][str(s.plat[ix])] = exp
    s.expect['plat'][str(s.plat[ix])] = exp
    s.store['plat'][str(s.plat[ix])] = exp
    return exp


def compare_plat(s,market):
    #print ' compare begin'
    if len(market.plats) > 0: #If there are any platforms, try and check
        b,bids,td=[],[],len(market.devs)
        tech = [float(i.release_d**2) for i in market.plats if i.ID  \
        not in market.retired_plat and i.ID in market.released_plat]
        #Get normalized technology for released platforms
        norm_tech = {str(i.ID):float(i.release_d**2)/max(tech) for \
            i in market.plats if i.ID not in market.retired_plat and \
            i.ID in market.released_plat}
        #Get expected/evaluated benefit
        for target in market.plats:
        #Cant evaluate those that already bought
          if s.bought['plat'][target.ID] == False:
            unplayed_games = len([i for i in target.announced_games \
            if i not in s.games])
            total_games = len(target.announced_games)
```

```
            if target.ID in market.released_plat and target.ID \
            not in market.retired_plat:
                ben = ((float(unplayed_games)/(total_games+1))+ \
                       float(s.expect['plat'][str(target.ID)])+ \
                       norm_tech[target.ID]
                tben = ben-target.consumerprice
                if tben > 0:
                    b.append(tben)
                    bids.append(target.ID)

        #Is there any good candidate?
        if len(b) > 0:
            want = bids[b.index(max(b))]
            if b.count(b[b.index(max(b))]) == 1:
                s.prospect = str(want)

#IV - Purchase platform.
def go_buy(s,ix,market):
    if rd.random() < s.wealth:
        s.plat[ix] = str(s.prospect)
        #Initial usage motivation
        s.consumed = 8
        s.consumeme = True
        for platform in market.plats:
            if platform.ID == s.plat[ix] and platform.ID not in \
               market.retired_plat and platform.ID not in s.old_plat:
                s.bought['plat'][s.plat[ix]] = True
                s.adopt['plat'][s.plat[ix]] = 1
```

```
                platform.hwsales_step += 1
                platform.users += 1
                exp = s.experience_plat(market,ix,s.plat[ix])
                market.disadoptersall.append(exp)
                if exp < 0:
                    s.adopt['plat'][s.plat[ix]] = 0
                    s.old_plat.append(s.plat[ix])
                    s.old_manuf = str(s.plat[ix])[0]
                    platform.users -= 1
                    s.plat[ix],s.consumeme = None,False
                    s.playing = False
                break
        s.prospect = None

#V - Purchase games.
def choose_game_to_buy(s,market):
    try:
        for ps in market.plats:
                if ps.ID in s.plat:
                    games_in_plat = ps.games.keys()
#game_val = {g:s.expect['game'][g] for g in games_in_plat if  \
        g not in s.games}
        game_val = [k for k,v in sorted(s.expect['game'].iteritems(),
            key=lambda (k,v): (v,k), reverse=True) if k not \
            in s.games and v > 0 and k[:3] in s.plat]
        if len(game_val) == 0:
            buygames = [None]
```

```
    else:
        buygames = game_val
    buygame = buygames[0]
        #Old part
    if buygame != None and buygame in market.games.keys() and \
        market.games[buygame][0] in s.plat:
        #Get game features
        game_value = market.games_features[buygame]

        utility = s.perceive(game_value)
        if utility > 0:#Buy game
            s.games.append(buygame)
            dev = market.games[buygame][1]
            market.devs[dev].unit_games[buygame] += 1

            #Experience the game (get dot product utility)
            exp = s.post_evaluation(game_value)
            s.experience['game'][buygame] = exp
            s.expect['game'][buygame] = exp

    #If experience is positive, consume more and start playing.
            if s.experience['game'][buygame] > 0:
                s.consumed += s.consume_rate
                s.playing = True
        elif utility < 0:
            s.experience['game'][buygame] = utility
            s.expect['game'][buygame] = utility
except Exception as e:
```

```
            print e
```

A.4 Platform Class.

```
class thePrincipal(object):
    def __init__(s,ID,price,time,releases,features='uniform', \
                 release_time=None,massinf=1):
        s.ID = str(ID)
        s.plat,s.games = [],[]              #no plat, no plat games
        s.iplat,s.igames = ['0'],['0-0']    #on development
        s.devs = [ID]                       #first party development
        s.users,s.hwsales,s.swsales = [],[],[]   #Userbase data
        s.releases = releases    #Number of Generations to release
        s.features = features
        s.expect = 0.01

        if release_time == None:
            s.release_d = [rd.randint(10+(150*i),10+time+(150*i+1)) \
            for i in range(releases)]     #Release steps list
        else:
            s.release_d = [release_time*((i+1)) for i in range(releases)]

        s.mkt_operation,s.mkt_rec = 0,[]
        s.mkt_range = massinf
        s.consumerprice,s.revenue = price,0

    def step(s,market):
        if len(s.release_d) > 0:
            if market.steps >= int(s.release_d[0]-52) and \
```

```
            s.releases > 0: s.announce(market)    #Platform Announce
        if market.steps == s.release_d[0] and \
            s.releases > 0: s.release(market)     #Platform Release
    #Promote platform
    s.marketing(market)
    s.mkt_rec.append(s.mkt_operation)

def marketing(s,market):
    if s.mkt_operation > 0:                        #Declines all steps.
        s.mkt_operation -= 1                       #Lose marketing

        if s.mkt_operation < 26+52:
          pick_cons = rd.sample(market.cons,int(len(market.cons)*\
                                                 s.mkt_range))
          for con in pick_cons:
            if market.cons[con.ID].adopt['plat'][str(s.plat[-1])] == 0:
                influence = np.clip(market.cons[con.ID].expect['plat']\
                                    [str(s.plat[-1])]+s.expect,-1,1)
                market.cons[con.ID].expect['plat']\
                [str(s.plat[-1])] = influence

def announce(s,market):
    if any(p not in market.announced_plat for p in s.plat)  \
    or s.plat==[]:
        s.mkt_operation += 26+52+52    #Mkting + 100
        s.plat.append(str(s.ID)+'_'+str(len(s.plat)))
        market.announced_plat.append(str(s.plat[-1]))
        for c in market.cons:
```

```
            c.experience['plat'][str(s.plat[-1])] = 0
            c.adopt['plat'][str(s.plat[-1])] = 0
            c.expect['plat'][str(s.plat[-1])] = 0
            c.old_expect['plat'][str(s.plat[-1])] = 0
            c.bought['plat'][str(s.plat[-1])] = 0
            c.store['plat'][str(s.plat[-1])] = 0
            if rd.random() < 0.05:
                c.expect['plat'][str(s.plat[-1])] = c.expect_m+0.1

        #Create the platform object in market
        new_plat = thePlat.thePlat(str(s.plat[-1]),
            s.release_d[0],s.features)
        market.plats.append(new_plat)
        market.plat_features[new_plat.ID] = new_plat.product

        #Initialize market adoption, devs, expect (for data record)
        market.record[new_plat.ID] = [0]*market.steps
        market.dev_rec[new_plat.ID] = [0]*market.steps
        market.expec_rec[new_plat.ID] = [0]*market.steps

def release(s,market):
    expects = [c.expect['plat'][str(s.plat[-1])] for \
        c in market.cons]
    expects.sort()
    top2 = int(len(expects)*.98)
    innovator_trsh = expects[top2]
    for c in market.cons:
        if c.expect['plat'][str(s.plat[-1])] > innovator_trsh:
```

```
                c.prospect = str(s.plat[-1])
        market.released_plat.append(str(s.plat[-1]))
        del s.release_d[0]
        s.releases -= 1
```

A.5 Publisher class.

```
default_dev_time = 52


class theDev(object):
    #initialization of agent parameters and memory
    def __init__(s,ID,bound=0.1,massinf=1.,feat_type='uniform',feat_n=2):
        s.ID = ID               #ID
        s.dev_time = {}
        s.bound = bound         #Market sampling boundary
        s.feat_type,s.feat_n = feat_type,feat_n

        #record keeping
        s.plats,s.games = [],0
        s.revenue = 0
        s.unit_games = {}
        s.unit_games_ts = {}
        s.unit_games_time = {}
        s.unit_post10weeks = {}
        s.old_adoption = []

        #working variables
        s.license_lim = 3       #license restrictions
        s.can_develop = True
```

```
        s.game_name = {}        #temporal games names

        s.consumer_prospects = []
        s.avg_prospects = []

    def announce_game(s,plat,market):
        s.can_develop = True
        s.game_name[plat] = str(plat)+str(s.ID)+str(s.games)
        for pp in market.plats:
            if pp.ID == plat:
                pp.announced_games.append(s.game_name[plat])
        for c in market.cons:
            c.expect['game'][str(s.game_name[plat])] = 0
            c.experience['game'][str(s.game_name[plat])] = 0

    def develop_game(s,market,feat_type='uniform'):
        #get a 5 dimension array/vector
        if feat_type == 'uniform':
            game_factors = [1]*(s.feat_n)+[rd.uniform(-1,1) for i in \
                               range(10-s.feat_n)]
        elif feat_type == 'good':
            game_factors = [1  for i in range(10)]
        elif feat_type == 'bad':
            game_factors = [-1  for i in range(10)]
        else:
            game_factors = feat_type
        s.games += 1
        return game_factors
```

```
def promote_game(s,plat,market):
    for c in market.cons:
        if rd.random() < 0.01:
            c.expect['game'][str(s.game_name[plat])] += 0.01

def step(s,market):
    for g,g_units in s.unit_games.items():
        s.unit_games_ts[g].append(g_units)
        if len(s.unit_games_ts[g]) > 50:
            s.unit_post10weeks[g] = g_units

    #New step (Old in Ver 2.0)
    if len(s.plats) > 0:
        for p in s.plats:
          if s.dev_time[p] > 0:
            s.can_develop = False
            s.dev_time[p] -= 1
            s.promote_game(p,market)
            if s.dev_time[p] == 0:
                for ps in market.plats:
                  if ps.ID == p:
                    s.old_adoption = s.old_adoption + [p]
                    s.plats.remove(p)
                    s.unit_games[str(s.game_name[p])] = 0
                    s.unit_games_ts[str(s.game_name[p])] = []
                    s.unit_games_time[str(s.game_name[p])] \
                    = market.steps
```

```
                game_features = \
                s.develop_game(market,feat_type=s.feat_type)
                ps.games[s.game_name[p]] = game_features
                market.games_features[s.game_name[p]] = \
                game_features
                market.games[s.game_name[p]] = [ps.ID,s.ID]

                ps.devs.remove(s.ID)
                break
    else:
        s.can_develop = True
        if s.ID in market.licensed or market.steps > 10:
          if rd.random() < 0.1 and s.can_develop == True and \
          len(market.plats) > 0 and len(s.plats) < s.license_lim:
            s.evaluate_plat(market)


def evaluate_plat(s,market):
    #Evaluate sample of consumers.
    user_dev_ratio,dev_cost = [],[]
    for p in market.plats:
      if p.ID in market.retired_plat:
        pass
      else:
        user_adopt = 0
        user_expect = np.mean([float(c.expect['plat'][str(p.ID)]) \
            for c in market.cons if rd.random() < s.bound])
        devs = len([this.devs for this in market.plats \
                if p.ID == this.ID][0])
```

```
            user_dev_ratio.append(float(user_adopt+user_expect)/ \
                float(devs+1))
            if devs < 0:
                print user_adopt,user_expect
                print '\n'
            #Missing license cost or dev cost
            if p.ID == '0_0':
                dev_cost.append(0.02)
            else:
                dev_cost.append(0)
        s.consumer_prospects.append(user_dev_ratio)

#Dev platform adoption with Multi - Homing (Chapter 3, Ver 3.0)
        try:
            want_list = [float(user_dev_ratio[i]) - float(dev_cost[i]) \
                for i in range(len(user_dev_ratio))]
            want_list2 = list(np.around(want_list,5))
            want_list = [float(i) for i in want_list2]
            want_list2.sort(reverse=True)
            multi_homing = 2
            want = [want_list.index(ww) for ww \
                in want_list2[:multi_homing]]
        except:
            print 'Developer - Error on getting the best platforms.'

        exclusivity = iter(market.exclusivity)
        if len(want) > 0:
            for w in want:
```

```
if market.plats[w].total_licenses > \
len(market.plats[w].devs):
    if w not in market.retired_plat:
        market.plats[w].devs.append(s.ID)
        new_plat = market.plats[w].ID
        s.plats.append(new_plat)
        exc = exclusivity.next()
        s.dev_time[new_plat] = rd.randint(40+exc,\
                  default_dev_time+exc)
        s.announce_game(new_plat,market)
        #print s.game_name[new_plat]
        return
```

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Curriculum Vitae

E. André L'Huillier graduated from The Mackay School, Viña del Mar, Chile, in 2003. After achieving his degree in Humanities from Universidad Andrés Bello in 2007, he received a Bachelor of Arts in Psychology and Master of Arts in Consumer Behavior from Universidad Adolfo Ibañez in 2012. After working in market research for two years he decided to pursue a Ph.D. in Computational Social Science at George Mason University.