Junior Management Science 6(3) (2021) 547-567

Junior Management Science

journal homepage: www.jums.academy

The Impact of Community Involvement on Game Life-Cycle: Evidence based on Gaming Platform Steam

Tim Leonard Hermes

Ludwig-Maximilians-Universität München

Abstract

Later stages of the product life-cycle are characterized by diminishing sales and declining prices. Especially firms with substantial product development costs, as is the case in the video game industry, are dependent on long product life-cycles to amortize initial costs. This confronts firms with the fundamental challenge of maintaining the value of their product from the consumer's perspective and thus delaying the natural price decline. We investigate whether product features that facilitate community involvement and interaction are an effective means to keep the product stimulating and relevant in the long run. Using extensive data from the PC video game market, we show that the inclusion of interactive, community-engaging features allows firms to both charge higher prices and delay the natural price decline of their product. However, for one of the investigated features we find the opposite effect, which we explain by subsequent analysis. Thereby, we gain valuable insights into the importance of robustly designed incentive systems in community-focused features. Our findings could help firms in their efforts to design attractive and economically viable products with prolonged life-cycles.

Keywords: Product life-cycle; digital goods pricing; user communities; co-creation; digital gaming platforms.

1. Introduction

Every product is subject to a life-cycle (Levitt, 1965). This applies to digital products just as much as to physical products. Although they do not age through wear and tear, they fall victim to psychological obsolescence (Park, 2010). Later stages of the product life-cycle are characterized by diminishing sales and declining prices (Golder & Tellis, 2003). From an economic point of view, a product's life-cycle ends when it no longer generates revenue. While progressive digitization of content substantially reduced marginal cost, there are still many digital products whose consumption is preceded by significant fixed costs, be it apps, movies, music or video games (Shy, 2001, p. 182). This constitutes the highly challenging task for firms to ensure long life-cycles and thereby amortize initial costs.

Extending the life-cycle translates into remaining relevant from the customer's perspective by offering continuous high value, which in turn allows firms to delay the natural price decline of their product. While traditional quality features of a product, such as the graphic quality of a video game, inevitably become obsolete with age, firms are increasingly turning their attention to product features that generate long-term stimulation and relevance. In the age of connectedness, it is the interactive, community-involving features that drive ongoing engagement (Von Hippel & Katz, 2002). In theory, such "Community Features" empower users to interact, set their own impulses, exchange ideas and give feedback. Thus, the community becomes a living "sounding board" which keeps the product vibrant and dynamic in the long run. Thereby, firms hope to maintain the value of the product from the consumer's perspective over the product life-cycle, and to capture it through higher prices.

In this context we attempt to address the **research question** of how Community Involvement influences price setting of firms on digital platforms? We investigate this question using the PC video game market as a relevant example, for four reasons. First, from an economic standpoint, video gaming has matured into a worldwide market worth 130B USD with an annual growth rate of 5.8% over the last five years, surpassing other two-sided markets such as music, cinema, TV or radio (PwC, 2019). Further, it is predicted that within the next five years consumers will spend an average of 25% more time annually on video games, leaving the growth rates

DOI: https://doi.org/10.5282/jums/v6i3pp547-567

of any other digital platforms like music streaming and social networking behind (Clarefield, 2018; PwC, 2017). Second, from a practical standpoint, we argue that long life-cycles are of particular relevance here. Unlike many other types of digital content, consumption is preceded by years of expensive development. Bankruptcies of developers who were unable to amortize their game during its lifespan are the pervasive reality (Leibovitz, 2013). Third, digital gaming platforms share many characteristics of efficient markets, most notably, many suppliers and consumers, low barriers to entry, fairly rational consumers, intense competition, high transparency and independent pricing by suppliers (see Chapter 3: Industry Background). This makes them an intriguing object of investigation as a representative for other digital platforms. Lastly, from a market dynamics standpoint, the video game industry is currently undergoing an upheaval that challenges the previous understanding of the term "gaming platform". Previously, platforms in the video game context were mostly understood as physical goods in the form of consoles, which act as an interface between game developers and players. Recently, through digitization of content, advanced digital rights management systems and higher performance of personal computers, we have witnessed the rise of "digital gaming platforms", allowing developers to publish PC games cheaply and consumers to buy and play them directly on the platform (Jöckel, Will, & Schwarzer, 2008). These new digital gaming platforms, which act as a central hub for millions of players and thousands of developers, allow developers to involve their community in entirely new ways. We are focusing on the pioneering and largest platform "Steam".

For this research we are investigating three novel methods that game developers can employ to promote player interaction and involvement. Specifically, we look at three Community Features that allow players to (1) customize a game with own and peers' User Generated Content, (2) collect and trade virtual items and (3) complete game challenges and earn social status, respectively. We develop theory to argue that the inclusion of these Community Features in games allows developers to charge higher prices and delay the natural price decline over the life-cycle of their game.

To test this empirically, we collected five years worth of longitudinal data on pricing, game characteristics and player numbers for over 2,000 games on Steam. For Community Feature (1) and (3) we find that developers can both charge higher prices and delay the natural price decline. For feature (2) we find the opposite effect. We explain the unexpected latter result with a subsequent analysis. We discover that the feature was used in a different way than the platform Steam intended and point out the importance of designing robust incentive systems during the conception of Community Features. We thereby contribute to the sparse empirical research on the effects of Community Involvement on pricing in the context of digital platforms.

The rest of this paper is structured as follows. Chapter 2 presents an overview of the related literature on pricing, life-cycles and Community Involvement. Chapter 3 provides a closer look of digital gaming platforms and Steam. Chapter 4 develops theory and hypotheses. Chapter 5 describes methods used for data collecting and analysis, ventures an exploratory descriptive analysis and features our models. Chapter 6 presents results, while Chapter 7 discusses them and shows limitations. Finally, Chapter 8 concludes with implications and directions for future research.

2. Related Literature

Our study touches on a number of key theoretical concepts, mainly pricing, product life-cycle and Community Involvement in the context of digital platforms. We will give a brief overview of how these topics relate in previous literature.

2.1. Pricing and Product Life-Cycle

Literature on pricing of new products is vast and covers various aspects. In this chapter we provide a selective overview of pricing decisions over the life-cycle of a product. Two prominent pricing policies in particular have been much discussed in the literature: A strategy of high introductory prices that fall over time to skim off the demand, "price skimming", and the strategy of low initial prices to capture the market, "penetration pricing" (Chatterjee, 2009; Dean, 1976). We will mainly focus on skimming strategies. Also relevant is the abstract notion of product lifecycles. While definitions are often fuzzy, it most commonly describes the gaussian-like diffusion in form of sales of a product over time along with declining prices (Levitt, 1965).

Early studies show the effects pricing can have on the diffusion, i.e. sales, of a new product. Already Bass and Bultez (1982) found, using theoretical diffusion models, that prices should fall monotonously over time. Later, Krishnan, Bass, and Jain (1999) specified that a monotonically falling price is optimal, especially if the new product is confronted with a price-sensitive target group or if the use of the new product involves risk, e.g. lack of quality. This is in line with similar studies using diffusion models (Bass, 1980; Dolan & Jeuland, 1981; Kalish, 1983). Unlike previously discussed studies that assume monopolistic market situations, a more recent study in the context of oligopolistic market structures suggests that optimal prices drop to a lower level if the product is subject to a shorter life-cycle, i.e. speed of diffusion is higher (Dockner & Fruchter, 2004). The authors justify this by arguing that producers try to gain larger market shares in the face of a shortened product life through aggressive pricing.

These early studies have a few things in common: first, the optimal price is solved analytically in a theoretical model, second, the logic is not tested on real world data, and most importantly third, demand is assumed to be exogenous (i.e. given via diffusion mechanism) and undynamic (in terms of strategic response to producer pricing). Motivated by these deficits, Nair (2004) shows, based on data from the video games market, that over the life of a product, producers are confronted with consumers that have different willingness to pay. Those who attach high value to the product buy it early, while those with a low willingness to pay wait. According to Nair, companies thus have an incentive to reduce prices as the product ages to skim off individual willingness to pay with so-called intertemporal price discrimination. Interestingly, he further shows that consumer behavior can be rational and strategic by anticipating price reductions and postponing the purchase decisions. Foundational literature supports the notion of such heterogenous demand conditions and attributes them to varying consumer preferences, which translate into different anticipated utility and willingness to pay (Roberts & Lilien, 1993; Varian, 1992). Rietveld and Eggers (2018) show for the video game market that games encounter a heterogeneous audience over their life-cycle, starting with early adopters who are willing to experiment and have significantly higher willingness-to-pay and late adopters who are more risk-averse.

However, while all these studies recognize and model that consumers are heterogenous, they also base their analyses on the questionable assumption that perceived utility of a product is constant over time for each individual (Adner & Levinthal, 2001). Although preferences can be considered mostly static, products are not "fixed", Adner and Levinthal point out. Utility and therefore willingness to pay can be increased over time by continuously introducing more quality to the product (Adner & Levinthal, 2001). Unlike most other studies they deviate from the simplifying assumption of monopolistic market situations and show that constant "rejuvenation" is especially effective with increasing competition. Similarly, Weerahandi and Dalal (1992) adapt the usual diffusion models to include the effect of increased utility through product attributes on purchase decisions. In contrast to most aforementioned research, a more recent study deviates from the assumption of exogenous demand (i.e. diffusion mechanism), by forecasting sales of a product purely based on increased product utility over time (Fruchter & Orbach, 2008). They even go a step further as they also consider characteristics that constitute positive network externalities. Their findings suggest that prices can be held up if product characteristics are improved.

The previously discussed literature argues that continually falling prices are the optimal pricing policy. This is also observable in studies of the video game market (Liu, 2010; Nair, 2004) and in our video game data, too. However, we would like to briefly mention that penetration pricing, i.e. initially aggressive prices, can be observed in other contexts. For example, in the platform battle between Playstation and Nintendo, Liu (2010) shows that initial penetration pricing can foster essential indirect network effects between console and game developers in order to win the market.

From the previously considered studies, some overarching insights can be deduced: First, over the lifespan of a product, the optimal prices fall. Second, much of the price research looks at the impact of pricing (independent variable) on sales (dependent variable). Thus, price is usefully seen as a strategic marketing tool. In the following, we want to reverse the role of price and consider it as a measure of value for a product that should be maximized over the life-cycle. Third, there is little research on how the inclusion of value-generating product features can increase the willingness to pay over time and allow higher prices.

2.2. Community Involvement as Utility Dimension

There is diverse literature that investigates the influence of product characteristics on consumer utility and willingness to pay. For example, previous studies have investigated changes in utility and willingness to pay for changes in product characteristics for digital goods such as music downloads (Hahsler & Breidert, 2006), smartphones (Böhm, Adam, & Farrell, 2015), mobile service platforms (Nikou & et al., 2014), online banking services (Yusuf Dauda & Lee, 2015) and tablet news apps (Gundlach & Hofmann, 2017).

However, in this study we are interested in the effect of Community Features. We define Community Features as product features that involve the community and enable interactions between platform participants. They are particularly relevant in the context of platforms as they are used in interaction with other users and can hence exhibit considerable network utility, more discussed in Chapter 4: Theory and Hypotheses (Katz & Shapiro, 1985; Meyer, 2012). Nonetheless, we find that the influence of Community Features on utility is very rarely measured. As one of few, a study by Benlian, Vetter, and Hess (2010) shows that Community Features (e.g. playlist sharing) in music streaming have a positive effect on the willingness to pay, but less so than classic quality features (e.g. sound quality). A comparable study for online games shows that willingsness to pay is higher for Community Features (e.g. virtual chat rooms) and customization features (e.g. character creation) than for better quality features (e.g. graphic quality). This indicates that Community Involvement is valued differently depending on the product. Yet, both analyses only provide a static view on the value of these features. Two very recent studies on the video game market adopt a more dynamic view by showing that Community Features can have a lasting effect on the life-cycle of a product. First, a study of the video game market found that games with multiplayer functionality generate higher sales in later phases of the life-cycle (Marchand, 2016). Second, Rietveld and Eggers (2018) show for Free-To-Play Games on Steam that games with Community Features (online multiplayer) are much more likely to become a "killer app", measured by download numbers.

While multiplayer functionality in video games is a well-established way of letting individuals interact with each other and benefit from direct network effects, there are many other ways to involve the community that haven't been subject to much prior empirical research.

3. Industry Background

Traditionally, video gaming platforms have mainly been understood as physical goods in the form of consoles, which act as an interface between game developers and players. Thus, the video game market can be classified as a two-sided market, which facilitates interaction between complementors, i.e. producers of complementary products (game developers), and consumers (players) (Eisenmann, Parker, & Van Alstyne, 2006). The video game market is characterized by a number of features, most notably: indirect network effects, which suggest that the utility obtained by platform participants on one side depends on the number of complementary platform participants on the other side (Katz & Shapiro, 1985). Equally important are direct network effects, which state that the utility also depends on the number of participants on the same platform side (Shy, 2011). In addition, the traditional video game market is characterized by intense hardware standards battles (Gallagher & Park, 2002), varying inter-generational hardware compatibility (Claussen, Kretschmer, & Spengler, 2010), short and interdependent hardware and software life-cycles (Marchand, 2016), the phenomenon of multi-homing between platforms (Landsman, V. and Stremersch, S., 2011), heterogeneous consumer needs (Rietveld & Eggers, 2018) and the presence of high switching costs (Gallagher & Park, 2002).

However, the video games industry is currently undergoing a transformation that challenges the traditional understanding of the term "games platform". With the digitalization of content, advanced Digital Rights Management systems and increased performance of computers, a new intermediary has entered the market: so-called "Digital Game Distribution Platforms" allow developers to offer PC games at low cost and players to buy and play games directly on the platform (Jöckel et al., 2008). The pioneer and largest representative of such digital gaming platforms is Steam, with 40,000 games and 20M active players at peak times (Steamspy, 2020).

While these digital gaming platforms introduce many novelties, the central mechanics of the traditional gaming industry, such as network effects and game lifecycles, are preserved. Still, some rules are changing. First, there is hardly any dependency between hardware generations and games anymore, since the compatibility of PC games is not dependent on a specific hardware generation, as was usually the case with consoles (Marchand, 2016). This means that the life-cycle of games is not predefined by the life-cycle of hardware. Second, there are low barriers to entry, which gave rise to the genre of "indie" games (Lin, Bezemer, & Hassan, 2018). Small and semi-professional developers ("indie developers") are able to publish their game for a one-time payment of 100€ and get exposure to an audience of millions, whereas before only big software companies could afford development and were exploited by platform owners as the "money-making side" (Bowen Martin & Deuze, 2009; Steam, 2020d). Third, digital platforms are characterized by increased transparency, as prices and independent ratings are directly comparable, which was previously less feasible with analogue games. Fourth, Nair (2004) has already shown for the traditional video game industry that consumers can act rationally and strategically by anticipating price reductions and postponing purchases. It is likely that such rational consumer behavior increases in the face of greater market transparency on digital gaming platforms.

Given these attributes, digital gaming platforms share many characteristics of efficient markets; most notably, many suppliers and consumers, fairly rational consumers, low barriers to entry, intense competition, high transparency and independent pricing by suppliers (Bork, 1993). This makes Steam an intriguing object of investigation as a representative for other digital platforms.

Finally, these new digital gaming platforms, which act as a central hub for millions of players and thousands of developers, enable entirely new possibilities for interaction and Community Involvement. For example, in recent years Steam has developed a range of value-added services that game developers have been able to integrate voluntarily through a Software Development Kit. These features have been targeted at further involving players, or as Steam puts it in their developer documentation, "to increase engagement, encourage player interaction and motivate players to spend more of their time in-game" (Steam, 2020c). This is a prime example of a platform owner, aspiring to empower its complementors with powerful tools to sustain long-term utility of their content.

4. Theory and Hypotheses

In this study we investigate the influence of Community Involvement on the price-setting of companies. In the context of the PC video game industry, we look at three important ways in which developers let their players get involved and interact with each other. In the following, we take a closer look at these three ways and derive testable hypotheses. "Community Feature" is not an established term and is rarely used in the literature. For our study, we broadly define those product features as Community Features that engage users by enabling interactions between platform members. Platform members are both users and game developers.

4.1. Contributing User Generated Content: "Steam Workshop"

Giving users the opportunity to participate in product development, create complementary products, and modify existing products is not a new phenomenon. Chesbrough (2003) coined the term "open innovation" to describe how companies can better meet the needs of their target group by complementing their own innovation efforts with external user innovation. According to Urban and Von Hippel (1988), so-called lead users, i.e. users who feel the needs of the target group much earlier than the rest of the market, are of particular importance. Their contributions to the innovation process are considered more relevant and novel by other users (Lilien & et al., 2001; Schreier, 2007; Von Hippel, 1986).

User innovation has a long tradition in the video game market. Games have long sought to differentiate themselves in the face of intense competition and to maximize customer satisfaction by giving them a say in company decisions (Jeppesen, 2005; Koch & Bierbamer, 2016). For example, the success of bestseller “The Sims” is often explained by the richness of User Generated Content (e.g. game characters), which is estimated to account for up to 90%. (CERI, 2006; Banks, 2013). A case study of the game “Trackmania” concludes that the game’s unusually long life span can be explained by the fact that the developers allow users to continually expand the game, which has led to a self-sustaining ecosystem of over 100 community websites and 3 million active hobby developers (Koch & Bierbamer, 2016; Parmentier & Gandia, 2013).

Since 2011, Steam offers a marketplace called *Workshop*. Developers can offer a *Workshop* for their game, allowing users to create, share and integrate content such as characters, game items and levels. Currently, there are about 4,000 games using this functionality, compared to 200 in 2016. In addition, developers provide user toolkits, i.e. tools and guidelines that allow users to create new products, complementary products or modify existing ones (Von Hippel & Katz, 2002). In the context of Steam, developers provide their users with so-called Software Development Kits, a collection of game-specific developer tools that allow players to create compatible content for the game at hand. A positive side effect of *Workshop* is that the developer facilitates a community that acts like a living “sounding board”. It allows players to share best practices, allows mutual help and learning, which increases the value of the game (Humphreys, 2005; Jeppesen, 2005). It also creates bilateral communication and feedback mechanisms between developer and player.

Jeppesen (2004) argues that the value-added through the availability of User Generated Content is twofold. First, the game becomes more attractive through the fact that complementary, often free content is available. The many possibilities for “mix and match”, according to Jeppesen, keep the game young in the long term, which has a positive effect on sales, especially in later phases of life. Second, and less intuitively, the author shows that developers systematically integrate popular User Generated Content into their game. This suggests that such games continuously increase their value from the user’s perspective and are less likely to be out of touch with the needs of the target group. We found proof of this phenomenon in Steam’s Subscription Agreement: “In some cases, *Workshop* Contributions may be considered for incorporation by Valve or a third-party developer into a game” (Steam, 2020b).

Nevertheless, an extensive case-study, which conducted interviews with game industry executives and experts, reveals that the share of innovating players is low, whereas the vast majority are not willing “to improve or modify or exchange with others” (Burger-Helmchen & Cohendet, 2011). Further, interviews with these regular players indicate that content from others is occasionally integrated and may lead to higher satisfaction and loyalty. However, previous research has shown that the quality of User Generated Content varies greatly (Lastowka, 2007). Thus, it is possible that users have bad experiences due to bugs, incompatibility, malware or offensive content (e.g. pornography), which negatively rubs off on the value of the underlying game. Steam counteracts this with rating systems, Steam moderators and the possibility for developers to curate contributions beforehand. However, it is unclear how many developers use this, given the effort involved.

When studying the motivation behind User Generated Content, we must distinguish between extrinsic and intrinsic factors. Extrinsic motivators include monetary incentives. For example, Steam lets users charge money for their creations to “allow mod [modification] makers the opportunity to work on their mods full time” (Steam Blog, 2015, 2020). This encountered great resistance from players, as user content has traditionally been free, which is why nowadays only a fraction of all content has to be paid for. According to Lerner and Triole (2002), building a reputation within the community is more important for users. In some cases, hobby developers even manage to break into developer jobs (Cadin, Guérin, & Defillippi, 2006; Poor, 2014). Nevertheless, intrinsic motivators seem to be the main driver for user innovation. A recent study, which conducted a survey of user innovators, identified joy, learning new skills and cognitive challenges as key (Koch & Kerschbaum, 2014). Franke and Von Hippel (2002) also point out the heterogeneity of user needs that cannot be met by standard software products. Users must therefore accept products that do not fit them well, which reduces their perceived value of the game. By offering toolkits, users get a voice and can tailor the product to their needs, whereby lead users benefit directly as they bring the necessary skills and resources, and other users indirectly by using the shared content (Franke & Von Hippel, 2002; Koch & Bierbamer, 2016).

Koch and Bierbamer (2016) are able to show for a small sample of games that the ability to create User Generated Content has a positive influence on the rating of a game. We investigate whether this higher satisfaction can be exploited with higher prices and therefore formulate the hypotheses:

> **H1a** *Enabling players to create own game content and enjoy their peers’ content via Workshop allows developers to charge higher prices.*

> **H1b** *Enabling players to create own game content and enjoy their peers’ content via Workshop allows developers to delay the price decline of their game.*

We know that the full effect of User Generated Content is achieved when it not only helps one individual to customize their game, but is also available to all others, whereby everyone benefits in form of network utility (Katz & Shapiro, 1985). It can therefore be assumed that a larger community will benefit more from the possibility of creating User Generated Content. We therefore formulate:

> **H1c** *A larger player community allows developers to charge higher prices for enabling players to create and share content.*

4.2. Collecting and Trading Virtual Items: "Steam Tradingcards"

Virtual items that players can earn, collect and trade have become an integral part of online games. They can take many different forms, such as in-game items, trophies or trading cards, and can entail diverse functionalities, benefits and values. Since 2013, Steam has been offering developers the opportunity to create game-specific *Tradingcards*. Some of the cards are given to players at random intervals during the game, while the remaining cards must be acquired by trading with other players on Steam (or buying them with virtual Steam money) to get a complete set. This set can then be displayed on the profile or exchanged for tradable benefits such as badges, personalized Steam profile backgrounds and game coupons (Steam, 2020a). About 9,000 games offer *Tradingcards*, which is about 20% of all games (Steam Card Exchange, 2020).

A large number of studies have examined the psychological stimuli triggered by virtual goods as well as the needs these goods satisfy. Bostan (2009) argues that players satisfy materialistic needs by possessing virtual goods, just as they do in the physical world. Some players spend substantial amounts of time amassing items to show them off, compare and trade them (Guo & Barnes, 2007; Yee, 2006). Such collectors often feel a strong desire for completeness (Danet & Katriel, 1994). Steam takes advantage of this by requiring players to have a full set of cards to reap the full benefits. This "un-locking mechanism" evokes anticipation and player interest in the long-term (Hallford & Lamothe, 2001; Wang & Sun, 2011). It is also conceivable that less mainstream games will become disproportionately more attractive through *Tradingcards*. For collectors, their cards are particularly valuable due to their rarity (Hamari & Lehdonvirta, 2010).

Formanek (1994) argues that collectibles also have a sentimental value as they remind of successful gaming experiences. In the case of Steam, *Tradingcards* can be a personal expression allowing a player to publicly identify with a game, signal one's interests and be part of a certain gaming community (Wang & Sun, 2011).

In the case of Steam, the incentives go beyond the mere possession of items. Players can use their cards to customize profile backgrounds, generate badges, and use rare emoticons while chatting, thereby "cosmetically" differentiating themselves. While this satisfies intrinsic needs for customization (Guo & Barnes, 2007), it also creates a "visual authority" over others, which many players appreciate, according to a survey of 300 players (Park & Lee, 2011).

Getting a full deck of cards is only possible by trading with others. Thereby, Steam adds a social dimension to a game. Given that social interaction is one of the most important gratifications of gaming, a positive influence on the value of a game can be expected, especially for single-player games (Scharkow, 2015). However, it is possible that rewards for activities outside the game, i.e. trading, or through mere playing time are perceived as unfair. Steam counteracts this by offering rewards that are only "cosmetic" and not functional, thereby persevering performance-oriented game mechanics.

Offering rewards at random times during the game has a gambling character, which makes such games exciting and addictive (Wang & Sun, 2011). Steam takes advantage of this logic by distributing cards at unknown times. However, in extreme cases, according to Rozin (2000), this can have negative effects on the gaming experience if the time of the reward is not predictable at all.

Virtual items can also be extrinsically motivating. Castronova (2005, p. 19) exemplifies the value virtual assets can have by showing that the multiplayer game Everquest is amongst the 80 largest economies in the world and its currency is more valuable than the Yen. Whang and Kim (2005) use a survey of nearly 5,000 players to show that some players see collectibles as a pure investment with value appreciation. Rare cards on Steam also embody enormous monetary value. They can be exchanged for virtual money on Steam, exchanged for real money on eBay or an enormous ecosystem at dedicated websites (e.g. steamcardexchange.net), as well as converted into expensive games.

Based on intrinsic and extrinsic motivators, we formulate the following hypotheses:

> **H2a** *Enabling players to collect and trade virtual items in form of Tradingcards allows developers to charge higher prices.*

> **H2b** *Enabling players to collect and trade virtual items in form of Tradingcards allows developers to delay the price decline of their game.*

4.3. Mastering Challenges and Earning Status: "Steam Achievements"

There is a wide variety of reward-based systems that target intrinsic and extrinsic motivations to motivate individuals towards high performance, commitment and achievement of goals (Farzan & et al., 2008). The influence of rewards such as virtual badges, points or rankings has previously been investigated by empirical studies for a variety of areas, for example enterprise social networks (Farzan & et al., 2008; Thom, Millen, & DiMicco, 2012), collaborative ideation tools (Jung, Schneider, & Valacich, 2010), e-learning tools (Denny, 2013), peer lending platforms (Hamari, 2013) and image tagging platforms (Mekler, Brühlmann, Opwis, & Tuch, 2013).

The games industry is considered the origin of such reward systems, hence the term "gamification" (Hamari, 2013). Since 2007, games on Steam have been able to reward players for particular accomplishments in the game with so-called *Achievements*. Developers define challenges of different difficulty, some of which are closely interwoven with the story, and some of which are mundane tasks. Upon completion, players will receive *Achievements*, essentially badges, which will be displayed on their Steam profile.

Based on a survey of 3,000 players, Yee (2006) identifies the feeling of achievement, which is expressed in advancement and competition, as one of the most important motivational factors in video games.

Literature suggests that rewards, such as *Achievements*, create value for players by setting clear goals (Farzan & et al., 2008; Hamari, 2013). This is in line with goal-setting theory, according to which individuals are motivated to high performance by challenging, short-term, measurable and specific goals (Locke & Latham, 1991, 2002). In addition, meaningful contextual challenges that teach players the possibilities of a game can bring considerable pleasure. Thus, *Achievements* are to be understood as a "guiding instrument" that helps the player to progress in the game (Hamari & Eranti, 2011; Montola, Nummenmaa, Lucero, Boberg, & Korhonen, 2009). Ideally, *Achievements* allow players to become completely immersed in the game and reach a mental "flow" state (Csikszentmihalyi, 1990; Wang & Sun, 2011).

Steam grants *Achievements* immediately after completing a task. According to Hamari (2013), the immediacy of positive feedback generates strong satisfaction and confirmation. This in turn has a positive influence on the perception of one's own competence, which can lead to intrinsic motivation (Mekler et al., 2013). More fundamental support for this is provided by reinforcement theory, which states that regular positive feedback strengthens the existing behavior (Luthans & Stajkovic, 1999). However, poorly designed achievement systems can cause frustration, for example, when *Achievements* are either too easy or too difficult to achieve (Juul, 2010), are used inflationarily or can be obtained through mundane tasks. In the case of Steam, where developers can define up to 500 *Achievements* per game, the quality and meaningfulness might suffer.

Nonetheless, *Achievements* are not an end in themselves. A large part of their value for individuals comes from the fact that they are publicly displayed. Thus, citetMekler2013 concluded based on a controlled experiment of letting people tag images that participants are motivated by comparability and display of performance. Similarly, Farzan and et al. (2008) demonstrates that individuals show more activity on an enterprise social network as a result of public status and points. These studies show that individuals in different contexts derive social value from features that allow comparison. This fulfills two needs central to gaming: "accumulating in-game symbols of wealth or status" and "the desire to challenge and compete with others", as Yee (2006) puts it. Barnett and Coulson (2010) note very practically that building a positive reputation and signaling competence is essential for being accepted into teams. Moreover, just as with virtual games-items, there are also systematic "Achievement Completists" who play a game until they have collected them all (Jakobsson, 2011, 2016). On Steam we find numerous groups like "100% Achievements Group" with thousands of members.

Finally, Hamari and Koivisto (2013) show in the context of a fitness social network that gamification features such as *Achievements* generate positive attitudes towards the product through increased reputation. This in turn leads to a higher probability of further use and significantly higher recommendation rates. Thus, *Achievements* can also be seen as an effective marketing instrument that increases the anticipated value of a game.

Based on previous theory, we formulate the following hypotheses:

> **H3a** *Enabling players to master game challenges and earn social status via Achievements allows developers to charge higher prices.*

> **H3b** *Enabling players to master game challenges and earn social status via Achievements allows developers to delay the price decline of their game.*

5. Empirical Setting

5.1. Data Sample

5.1.1. Data Collection

The data set for this study combines data from four different sources. Collecting data from different sources was necessary to build a comprehensive and, in terms of the research question, meaningful data set. As a first step, we identified the most popular game titles on Steam. We defined games as "popular" if they had at least 1,000 active players at any time since their release. This resulted in a list of 4,180 games. The reason for such a strict cut-off was the lack of data quality and availability for less popular games. Next, we obtained historical prices in USD for these games from the website "steamdb.info", which tracks prices for a variety of Steam games since November 2014. For this, we built a custom crawler with Python, which retrieved the price history for each game in our list. The purpose of the crawler was to automate an otherwise extremely time-consuming manual task, but we paid attention to slow website calls to stay well below the server's rate limit. Unsuccessful website requests, e.g. server errors, were logged and the call was repeated at a later time. The collection process took about 3.5 weeks. Ultimately, we were able to collect price histories for 3,801 games. 379 of these 3,801 games had incomplete histories because they were released before Steamdb started tracking prices, so we deleted them, resulting in a relevant sample of 2,784 games (see Figure 1). Another important part of the data set are the characteristics of games. Some of these characteristics were directly available via Steam's public developer API "api.steampowered.com", which we queried with a dedicated Python script. The other part of the game characteristics were obtained in a similar way from the website "steamspy.com", which crawls the Steam website at regular intervals. Finally, we retrieved historical player numbers for each game from the website "steamcharts.com", which documents these on a monthly basis for many Steam games since 2012.

5.1.2. Data Preparation

When obtaining the data, we made sure that all sources use official Steam Game IDs, which allowed us to easily

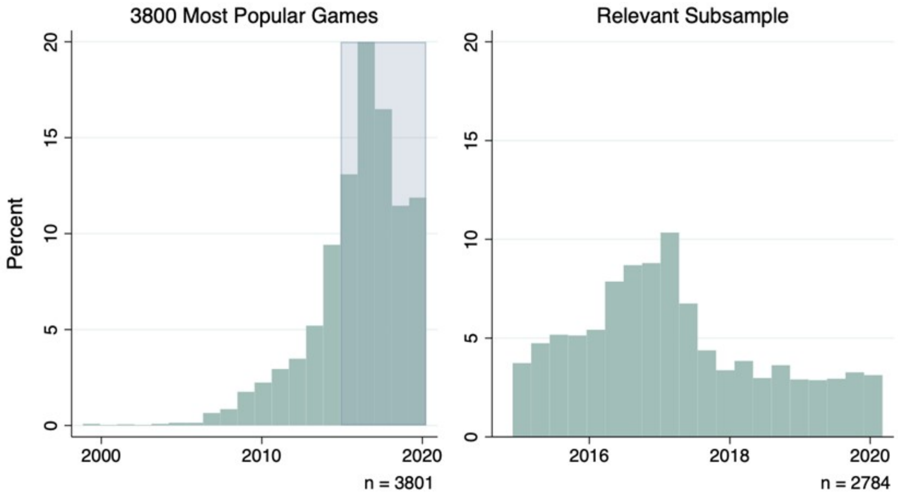

Figure 1: Distribution of Release Dates

merge the data into one large data set. From here, we identified a number of relevant cases that need to be treated differently (see Figure 2). Most importantly, we need to exclude games that have always been "free-to-play" from our sample, since a price of 0 does not reflect the value of the game, but rather indicates an alternative monetization strategy, for example via In-App-Purchases. For games that become free over time, we also assume a change in the monetization strategy and trim them from that point on. Games that retire at some point are continued with a price of 0 in the original sources, which is why we also trim them.

Game profiles on Steam are filled out manually by developers. As a result, they may fill in incomplete information when the game is released. For example, they may forget to indicate what genre the game belongs to or whether it has multiplayer functionality. Here, we use the swarm intelligence of the player base. Players can create "Tags" for each game that need to be upvoted by enough other players to appear on the profile. To increase the accuracy of variables, we linked user-defined tags to profile information.

Finally, we constructed three sub-datasets. This is necessary to answer different parts of the research question. Two are of cross-sectional structure, one of which looks at the time of release of the games, while the other compares all games at the same time-point in the present (March 2020). The third data set is panel structure and compares games over time.

5.2. Descriptive Evidence

Table 1 shows a condensed overview of the central variables across the three datasets. As we built three sub-datasets, we calculated three tables with summary statistics. Due to space restrictions, these tables can be found in the Appendix (see Table A1 for cross-sectional dataset "Release", Table A2 for cross-sectional dataset "Present", Table A3 for panel dataset).

Additionally, we take a first exploratory look at our data. Since game prices are of particular importance in our context, we will first look at the 16 (limited due to space) oldest games in our sample (see Figure 3).

While the limited number of games depicted does of course not represent all other games, we can nevertheless venture five important deductions: First, we see that in most cases the price declines over the years, which confirms that games are subject to a life-cycle. Second, we acknowledge that the rate of price decline varies greatly, some of them remaining very stable. Third, we see that price reduction is managed through sustained changes in the base price, not through discounts (represented by strong downward swings). Accordingly, the base price is a better, less volatile measure of value for a game. Fourth, we can see that games have fundamentally different price levels, e.g. some never go below $30, while others never go above $10.

Since Community Involvement is of particular importance, we also look at four features that game developers can use for this purpose. For sake of completeness, we show *Leaderboards* here, although we will limit our focus to the other three, as only they represent truly new approaches to Community Involvement. It turns out that developers integrate these features with varying frequency.

Next, we are interested to see if we can observe some indication that games with above features have different price patterns. For this purpose, we create two groups for each of the features (with and without feature) and calculate average prices for all games in the respective group for each day after release.

In fact, we can see big differences between the subgroups of each Community Feature. First, we see that the subgroups have different price levels across all features. Second, we can see that there also seem to be different price developments. Third, the feature *Tradingcards* is the only feature that performs worse than it's reference group.

The graphs should be interpreted with caution. The first impression could be misleading, as there are unobserved correlations and time effects, which we do not control at this point. However, we take this as an opportunity to take a

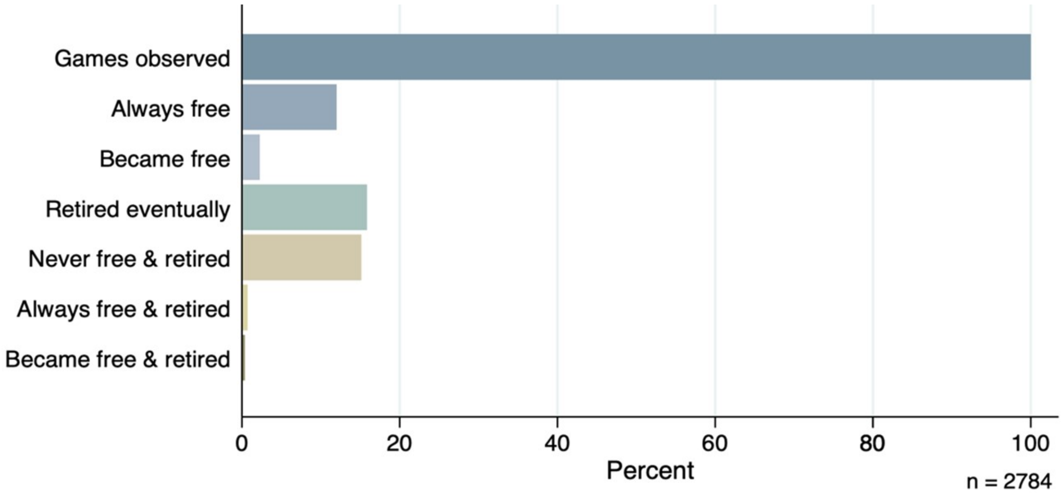

Figure 2: Categorization of noteworthy Cases

Table 1: Overview of Variables

Variable	Definition
Price	Price of a game (log)
Workshop	*User Generated Content*: Players can create game content & use others'
Tradingcards	*Virtual items*: Players can collect earn awards & display on profile
Achievements	*Challenges and Status*: Players can earn awards & display on profile
Leaderboards	Players can compare performance in rankings
Multiplayers	Game supports multiplayer
Controller Support	Game supports controllers
Cloud Gaming	Game has various cloud functionalities
TV Compatible	Game is playable on TV-Screen
Remote Gaming	Game is playable privately remotely with friends
In-app-purchase	Game offers players to buy game items
Number Languages	Number of available languages in game
Number Pictures	Number of pictures on store page to promote game
Number Trailers	Number of trailers on store page to promote game
Developer Experience	Number of games (Co-) developed so far
Publisher Experience	Number of games (Co-) published so far
Number Markets	Number of regions game is available
Platform Owner	Platform owner Valve developed the game
Genre	Game belongs to Action/Indie/Strategy/Simulation/Roleplay/ Casual/Nudity/Sport
Release Month	Release month of Games
Operating System	Game available on Windows/Mac/Linux or Combinations
User Rating	User rating for game
Number ratings	Number of total ratings for game
Average Playtime	Average individual playtime for a game to date
Number of DLC	Number of additional paid content available for game
Age	Age in days of game
Players Number	Average number of players for game over time(log)

Note: See Appendix Table A1, Table A2, Table A3 for more details & summary statistics

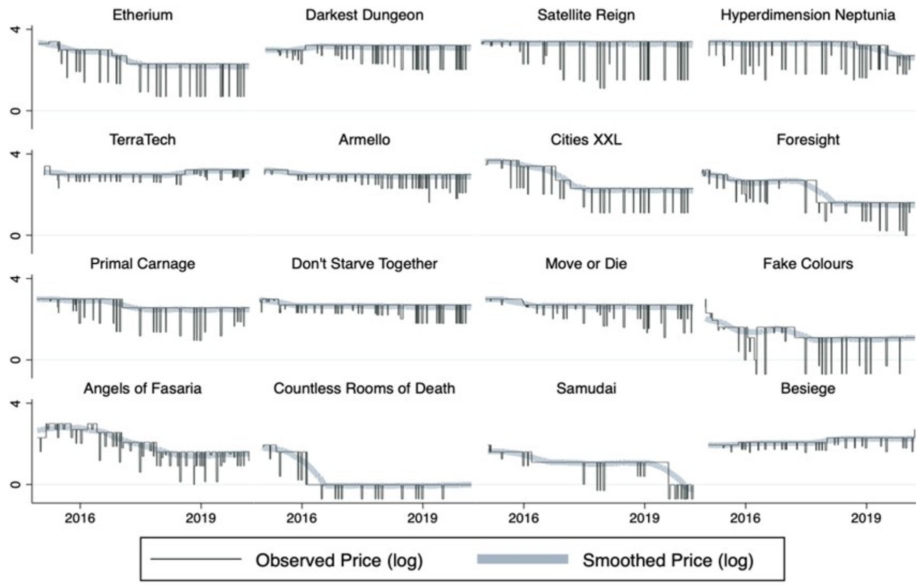

Figure 3: Price Development of earliest Games in Sample

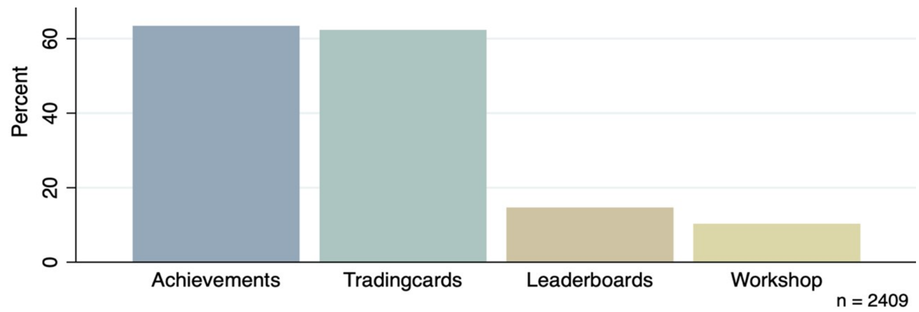

Figure 4: Proportion of Games with respective Community Feature

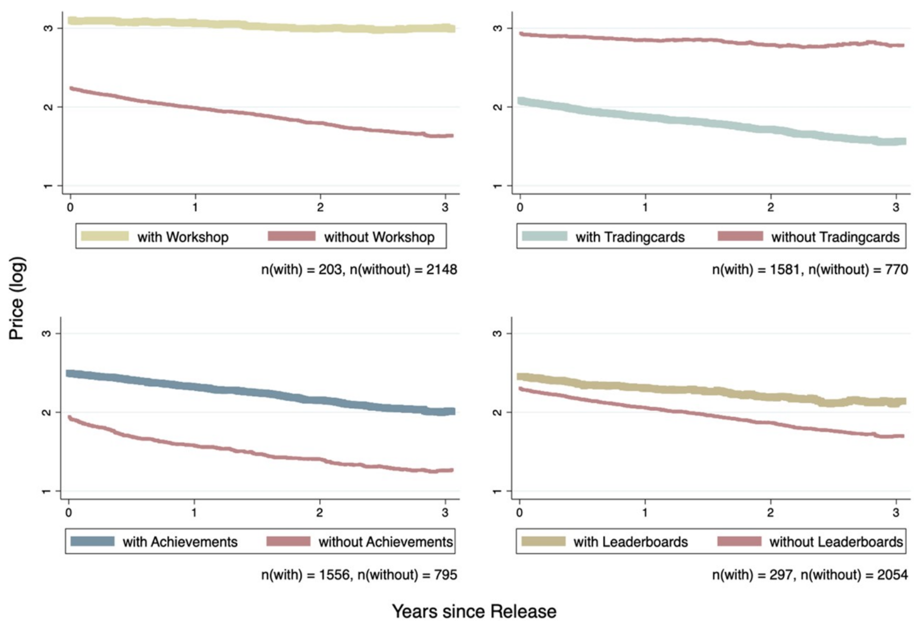

Figure 5: 3-year Price Development differentiated by Community Feature

closer look at the effect of Community Features on the lifecycle of a game.

5.3. Variables

5.3.1. Dependent Variables

The price of a game serves as a dependent variable across our analysis. Depending on the model, we either look at the price at a certain point in time, i.e. at release or present, or the price over time. Since price shows a right-skewed distribution (see Figure 6), we log-transform the price as recommended in literature (Osborne, 2010). In doing so, we strengthen the normal distribution of our Residuals (see Appendix Figure A1).

5.3.2. Independent Variables

The three Community Features, *Workshop*, *Tradingcards*, *Achievements* serve as independent variables in this study and are jointly included as Dummies. Since these three features are either implemented in a game or not, we investigate the effect of their existence on the Dependent Variable. Depending on the model, the variables are either included individually, i.e. additively, or each of them is included in interaction with a another variable, i.e. multiplicatively.

5.3.3. Control Variables

The controls we apply depend on the model. In our cross-sectional models, we employ controls to explain heterogeneity between games. Thus, we include a broad range of game characteristics that could have an impact on the quality, i.e. utility, perceived by the consumer (see Appendix Table A1 for a complete list). We also control for less tangible differences, such as increasing experience of developers and publishers over time, which could affect quality and promotion of a given game. Since we are interested in price as a value measure for game, we also control for supplementary monetization strategies such as In-App-Purchases, which might lead to a reduced price. In our panel models, we control for differences in games by including Fixed Effects, which account for all time-invariant characteristics. In addition, we control temporal factors in all models by including game age or a Dummy for each month, which accounts for both variance due to time trends and shocks. The latter is particularly important because part of our observations coincide with the outbreak of Covid-19.

5.4. Model Specification

In total, we specified four models. The first two models test H1a, H2a, H3a. We use OLS Models to exploit our data at two distinct points in time. Model 1 looks at the time of release of each game, hence we control *Release Month*.

$$\begin{aligned}
Price_{iRelease} = {} & \beta_0 + \beta_1 Workshop_i + \beta_2 Tradingcards \\
& + \beta_3 Achievements_i + \beta_4 DeveloperExperience_i \\
& + \beta_5 PublisherExperience_i \\
& + \beta_6 Platformowner_i + \beta_7 NumberTrailers_i \\
& + \beta_8 NumberPictures_i + \beta_9 NumberMarkets_i \\
& + \beta_{10} FeatureVector_i + \beta_{11} GenreVector_i \\
& + \beta_{12} OperatingsystemVector_i \\
& + \beta_{13} ReleaseMonthVector_i + \varepsilon_i
\end{aligned}$$

where i denotes a specific game; $FeatureVector_i$, $GenreVector_i$, $OperatingSystemVector_i$, $ReleaseMonth Vector_i$ are vectors of characteristics of a game (see footnotes[1234]); ε_i represents the residuals; $Workshop_i$, $Tradingcards_i$, $Achievements_i$ are the independent Dummy variables, coded 1 if the feature exists in game and 0 otherwise.

Model 2 compares all games at the present time (March 2020), which is why we control the *Age* (non-linear, see Appendix Figure A2) to account for different lifecycle stages. Further, we include additional variables that become relevant at a later point in game life: User Rating, Number of Reviews, Average Playtime, Number of DLC.

$$\begin{aligned}
Price_{i,Present} = {} & \beta_0 + \beta_1 Workshop_i + \beta_2 Tradingcards_i \\
& + \beta_3 Achievements_i + \beta_4 DeveloperExperience_i \\
& + \beta_5 PublisherExperience_i + \beta_6 PlatformOwner_i \\
& + \beta_7 NumberTrailers_i + \beta_8 NumberPictures_i \\
& + \beta_9 NumberMarkets_i + \beta_{10} UserRating_i \\
& + \beta_{12} NumberReviews_i + \beta_{12} AveragePlaytime_i \\
& + \beta_{13} NumberDLC_i + \beta_{14} GameAge_i \\
& + \beta_{15} (Age_i * Age_i) + \beta_{16} FeatureVector_i \\
& + \beta_{17} GenreVector_i \\
& + \beta_{18} OperatingSystemVector_i + \varepsilon_i
\end{aligned}$$

where i denotes a specific game; $FeatureVector_i$, $GenreVector_i$, $OperatingSystemVector_i$ are vectors of characteristics of a game (same as Model 1); ε_i represents the residuals; $Workshop_i$, $Tradingcards_i$, $Achievements_i$ are the independent Dummy variables, coded 1 if the feature exists in game and 0 otherwise. Both models use more conservative Robust Standard Errors to cater for slight heteroskedasticity, which a Breusch-Pagan test revealed

[1]Vector Features of game: Leaderboards, Multiplayer, Controller Support, Cloud Gaming, Virtual Reality, TV Compatible, Remote Gaming, In-App-Purchases, Number Languages

[2]Vector Genres of game: Action, Indie, Strategy, Simulation, Roleplay, Casual, Nudity, Sport, Racing

[3]Vector Operating Systems of game: Windows, Windows&Linux, Windows&Mac, Windows&Mac&Linux

[4]Vector Release Month of games: Month Dummies for period November 2014 – March 2020

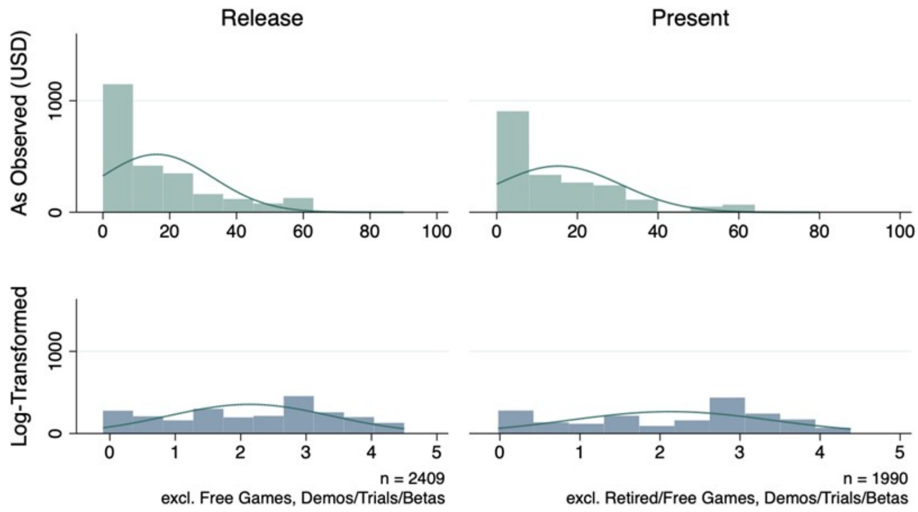

Figure 6: Distribution of Price at significant Time Points

(Breusch & Pagan, 1979). Further we calculated Variance Inflation Factors (VIFs) for our variables to ensure a lack of multicollinearity (see Appendix Table A4, Table A5). All factors are well below the commonly applied practice rule of 10 (Chatterjee & Hadi, 1986). While we do employ many variables, our variable-to-observation ratio is with 2,000 observations well below the most conservative ratio Tabachnick and Fidell (2007, p. 123) suggest.

Model 3 test H1b, H2b, H3b. Via a Hausman-Test, we tested the assumptions of applying a Panel OLS Random Effects Regression (i.e. individual game effects are uncorrelated with regressors), which allows time-invariant variables to be used in a regression (Hausman, 1978). As we couldn't reject the test-hypothesis of randomly distributed individual effects, we employ a Panel OLS Regression with Fixed Effects for games. Model 3 interacts *Age* of a game with each of the Community Features *Workshop*, *Tradingcards*, *Achievements*, which are time-invariant. Thereby, we examine whether games with these features are subject to different price development over *Age*. Further, we assume a different effect of *Player Numbers* depending on *Age*.

$$\begin{aligned} Price_{i,t} = \beta_0 &+ \beta_1(Workshop_i * Age_{i,t}) \\ &+ \beta_2(Tradingcards_i * Age_{i,t}) \\ &+ \beta_3(Achievements_i * Age_{i,t}) \\ &+ \beta_4(PlayerNumbers_{i,t} * Age_{i,t}) \\ &+ \beta_5 Age_{i,t} + \beta_6 PlayerNumbers_{i,t} + u_i + \varepsilon_{i,t} \end{aligned}$$

where i denotes a specific game, t a specific day, u_i the individual (fixed) effect of a game, and $\varepsilon_{i,t}$ the residuals.

Model 4 tests H1c. Here, we interact *Workshop* with *Player Numbers* to examine whether the effect of *Workshop* on price changes with more players or equivalently phrased, whether the effect of *Player Numbers* on price changes, given the existence of *Workshop* in a game.

$$\begin{aligned} Price_{i,t} = \beta_0 &+ \beta_1(Workshop_i * Age_{i,t}) \\ &+ \beta_2(Tradingcards_i * Age_{i,t}) \\ &+ \beta_3(Achievements_i * Age_{i,t}) \\ &+ \beta_4(Workshop_{i,t} * PlayerNumbers_{i,t}) \\ &+ \beta_5 Age_{i,t} + \beta_6 PlayerNumbers_{i,t} + u_i + \varepsilon_{i,t} \end{aligned}$$

where i denotes a specific game, t a specific day, u_i the individual (fixed) effect of a game, and $\varepsilon_{i,t}$ the residuals. To cater for potential heteroskedasticity and autocorrelation, we cluster Standard Errors on a game level in Model 3 and 4 (White, 1980, pp. 817). An alternative, which is not explored in the scope of this paper, is to use a model based on Baltagi (1999) who proposes a Fixed Effects Regression with Autoregression Type 1 Disturbance, suitable for large time dimensions.

6. Estimation Results

Table 2 and Table 3 at the end of this chapter provide a condensed overview of our results. Full reports are found in the Appendix. We present the results in order of our hypotheses.

H1a argued that games that include the possibility of User Generated Content via *Workshop* are priced at a higher level. We test this at two distinct timepoints: Model 1 looks at the price at release, while Model 2 looks at the price at present (March 2020). Our results show that games including *Workshop* demonstrate an on average 17% significantly higher release price and an on average 16% significantly higher present price, offering consistent support for H1a. We also found support for H1b in Model 3. Specifically, games with *Workshop* have on average 0.2% less price decline every month compared to games without (see Figure 7).

Lastly, in Model 4 we found a significant positive interaction between *Player Numbers* and *Workshop*, showing that

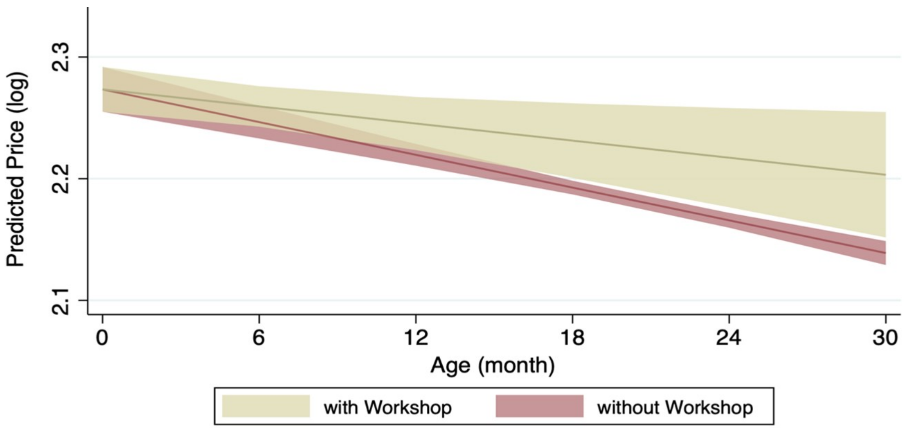

Figure 7: Price Development depending on Workshop Feature (95% CIs)

the effect of Player Number on price changes when the game includes Workshop, thus offering support for H1c (see Figure 9).

H2a argued that games that include the possibility of collecting and trading virtual items in Form of *Tradingcards* are priced at a higher level. Again, we tested this at release (Model 1) and present (Model 2). Contrary to our expectations, the feature *Tradingcards* exhibits a significantly negative effect on both the release price and present price. Games with *Tradingcards* have a on average 27% lower release price and 33% lower present price, leading us to reject H2a. Finally, we find with Model 3 that games with *Tradingcards* are subject to a greater price decline over time than games without (see Figure 10), which leads us to the reject H2b. Specifically, games with *Tradingcards* show an average of 0.3% more price decline every month compared to games without.

H3a argued that games that include the possibility of completing in-game challenges and earning social status via *Achievements* are priced at a higher level. We find a positive but, at the 5% level, just insignificant effect on release price (Model 1). However, the feature demonstrates a positive significant effect on present price, i.e. games with *Achievements* have a on average 12% higher present price (Model 2). This implies that H1c is only supported at an advanced life-cycle stage of a game. H3b is confirmed (Model 3), as we see less price decline with age for games with the feature (see Figure 11). Specifically, *Achievements* games show an average of 0.23% less price decline every month.

Beyond our Hypotheses, we also estimated the effect of *Player Numbers* on price and assumed that it changes over the life-cycle of a game, by interacting it with *Age*. We found that *Player Numbers* is negatively associated with price over most of a game's lifetime (Figure 13). In the Limitations (see Chapter 7), we will address this fact critically.

Finally, we conducted robustness checks on all models. For Model 1 and 2 by firstly taking up a reduced number of variables and secondly extending them with variables that represent less tangible user-defined characteristics about a game such as "Diffcult", "Classic" or "Family Friendly" (see Appendix Table A6, Table A7). For Model 3 and 4 we took up a reduced number of Variables (see Appendix Table A8). All checks show consistent results.

A condensed summary of previously discussed results is found in Table 2 and Table 3.

7. Discussion and Limitations

7.1. Discussion

In H1 we argued that developers who allow User Generated Content by including *Workshop* functionality can (a) charge higher prices compared to other games and (b) delay the natural price decline of their game. In essence, we justified this by the fact that players value the possibility to customize a game with their own and peers' content and thus keeping it engaging and stimulating in the long run. We wanted to know whether this higher perceived value can be exploited by developers in the form of higher prices. We tested H1a at two distinct time points: at release (Model 1), representing purely the developers perception of value, and at present (Model 2), representing a shared belief about the game, as players have been able to provide price feedback through either buying or not. We found consistent support for H1a by observing a higher price both at release (Model 1) and present (Model 2). Additionally, we found H1b, i.e. less price decline over time, confirmed, indicating that User Generated Content continually rejuvenates the game as it technically ages (see Figure 7). The support for H1c additionally shows that *Workshop* functionality provides users with network utility via indirect network effects. The effect of *Workshop* increases when a game has a larger player community, most likely as each player has more peer-content to integrate (see Figure 9).

In H2 we argued that developers who allow players to collect and trade virtual items in form of *Tradingcards* can (a) charge higher prices compared to other games and (b) delay the natural price decline of their game. Essentially, we hypothesized that players derive, amongst others, sentimental, monetary and social (e.g. status) value that developers exploit through higher prices. To our surprise, we found *Tradingcard* games have a lower price level, both at

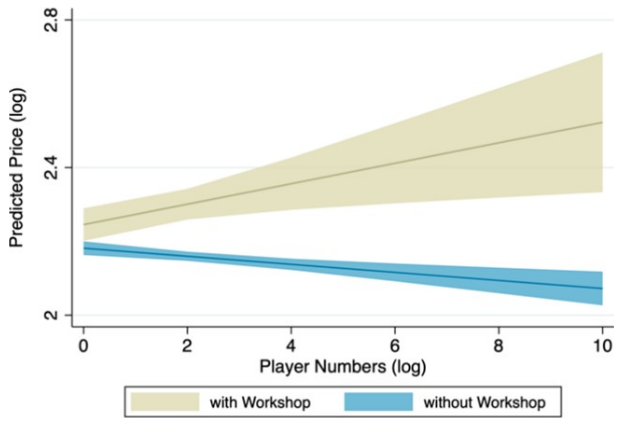

Figure 8: Price by Players dep. on Workshop

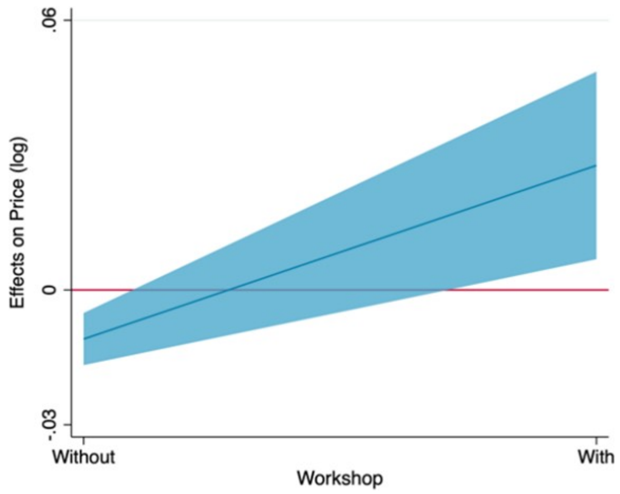

Figure 9: Effect of Players dep. on Workshop

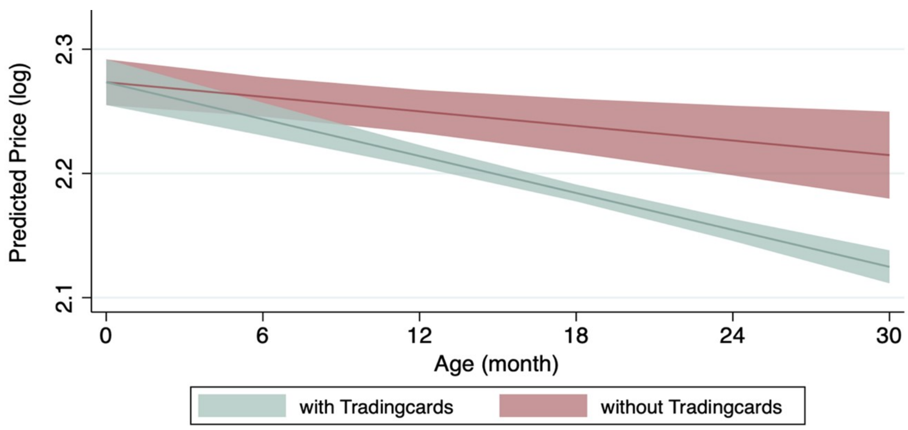

Figure 10: Price Development depending on Tradingcards Feature (95% CIs)

release and present. Additionally, they are also associated with a stronger price decline (see Figure 10). These finding are in sharp contrast to our theory and previous literature. Therefore, we venture another look at the mechanics of the feature to identify potential oddities that change the way the feature works in the context of Steam. We discovered that in the past, most recently in November 2019, Steam has banned large numbers of games that, as they explain vaguely, were "abusing Steam tools for financial gain" (PC Gamer, 2019). Through further research we found Reddit threads and an old Steam statement suggesting that some developers released low-cost games with *Tradingcards* functionality to distribute

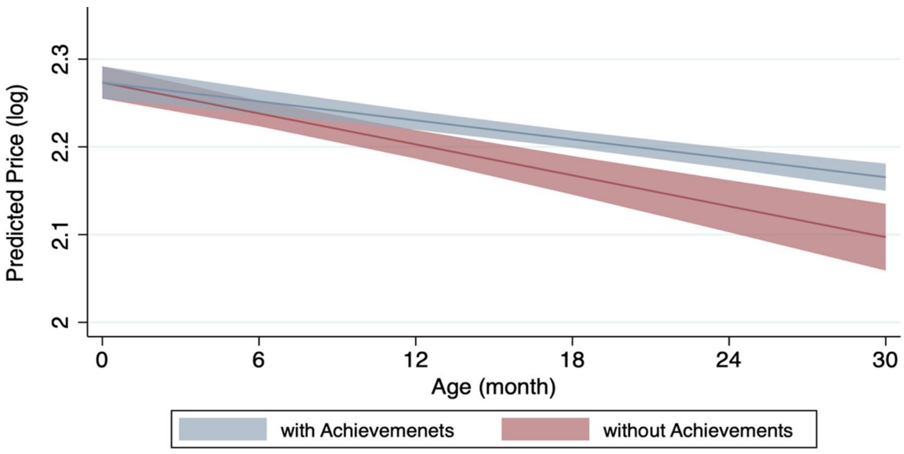

Figure 11: Price Development depending on Achievements Feature (95% CIs)

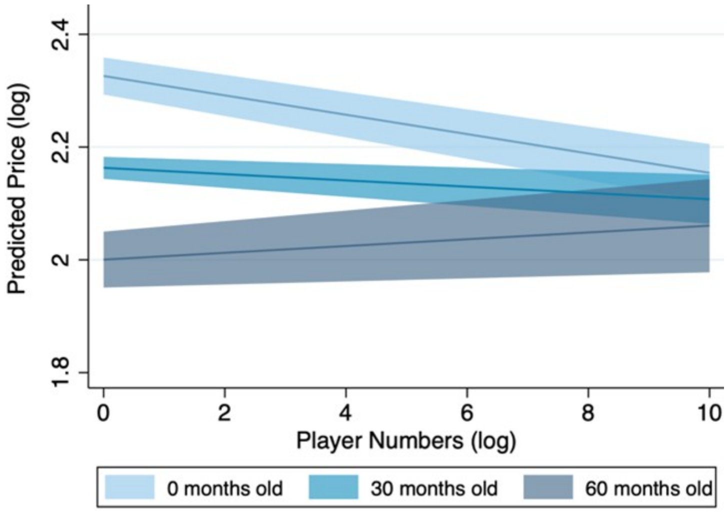

Figure 12: Price by Players for different Age

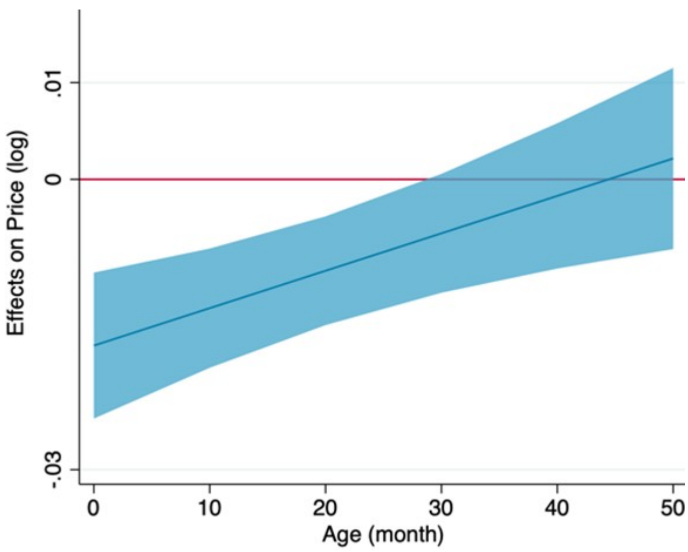

Figure 13: Effect of Players dep. on Age

Table 2: Effect of Community Features on Price Level

Model	1		2	
IndependentVariable	Price Release (log)		Price Present (log)	
Workshop	0.16**	(0.05)	0.15**	(0.06)
Tradingcards	-0.32***	(0.04)	-0.40***	(0.05)
Achievements	0.09	(0.04)	0.12*	(0.05)
N	2,029		1,763	
Adj.R^2	0.66		0.68	

Note: Full report see Appendix Table A6, Table A7. Robust SE in parentheses. ***p<0.001, **p<0.01, *p<0.5.

Table 3: Effect of Community Features on Price Development

Model	3		4	
IndependentVariable	Price (log)		Price (log)	
Age	-0.005***	(0.001)	-0.004***	(0.001)
*Age*Workshop*	0.002*	(0.001)	0.003**	(0.001)
*Age*Tradingcards*	-0.003***	(0.001)	-0.004***	(0.001)
*Age*Achievements*	0.002**	(0.001)	0.003**	(0.001)
PlayerNumbers	-0.017***	(0.004)	-0.011***	(0.003)
*PlayerNumbers*Age*	-0.000***	(0.000)		
*PlayerNumbers*Workshop*			0.039***	(0.011)
N	1,799,274		1,799,274	
Adj.R^2	0.08		0.07	

Note: Full report Appendix Table A8. Robust SE clustered on Game-level in parentheses. Age in Month, PlayerNumbers in log. ***p<0.001, **p<0.01, *p<0.5.

cards en masse to players or bots, and then profit from each trade through fees on their cards (Reddit, 2019; Steam Blog, 2017). A closer look at our sample confirms that in November a disproportionate amount or games that retired or, as we now know, were banned had *Tradingcards* as their only feature (see Figure 14). While this fact has compromised the expected effect of *Tradingcards* in our analysis, it does shed light on the importance of designing robust incentive systems when developing Community Features.

In H3, we argued that developers who allow players to complete in-game challenges and thereby earn social status via *Achievements* can (a) charge higher prices compared to other games and (b) delay the natural price decline of their game. At its core we justified this logic by assuming increased perceived value through serving intrinsic needs such as joy, feelings progression and accomplishment (see also goal-setting theory and reinforcement-theory) on the one hand, and extrinsic needs such as signaling competency and building social status on the other hand. In terms of H3a, we did not find significantly higher prices at the time of release, but at present. This discrepancy may indicate that developers, when setting the release price, initially underestimate the value that players gain from such functionality. A different explanation may be that developers also consider the amount of effort required to integrate certain functionalities. In contrast to *Workshop*, *Achievements* are very easy to integrate by defining a few simple challenges for the player. Lastly, we found H3b, i.e. less price decline over time, confirmed, indicating that challenges offer long-term value to the game (see Figure 11). This makes sense, since especially the extrinsic value (social status) that players derive from collecting *Achievements* is independent of game age, hence players are still interested in games at later life stages.

7.2. Limitations

First, in this study we investigate the influence of community features on pricing of games. It is based on the logic that ceteris paribus increased utility is expressed in increased willingness to pay, which developers capture through higher prices. The validity of this rationale is based on two assumptions. First, that the market is largely efficient, since only then will the equilibrium price reflect both supply and demand (aggregated willingness to pay). Although we show that digital gaming platforms share many elements of perfect markets (see Chapter 3: Industry Background), we are aware that no real-world market is perfect. Secondly, price is not only a measure of value but also a marketing tool. Thus, it is conceivable that developers may pursue penetration strategies via initial discounts or even pursue alternative monetization models. We control as much as possible

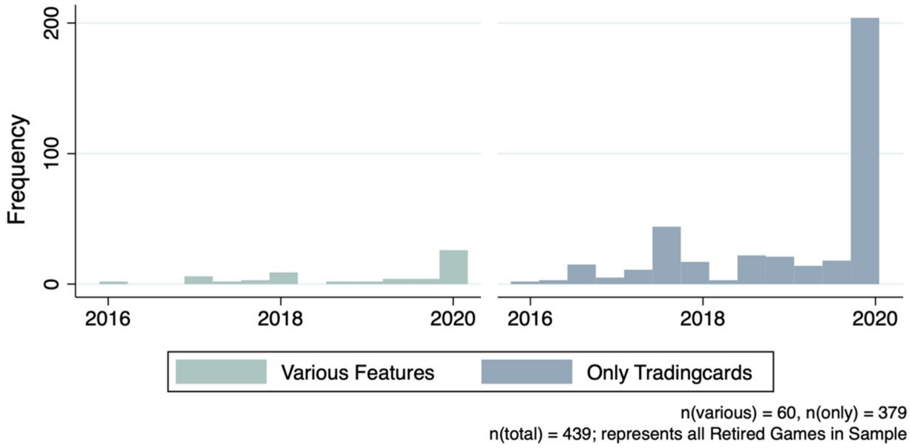

Figure 14: Distribution of Retired Games in Sample differentiated by Features

for such strategies by using, for example, the base price of a game, which ignores strategic short-term discounts and only reflects long-term price changes (see Figure 3). In addition, we control as much as possible for complementary monetization strategies, such as additional paid content (DLCs) or In-App-Purchases. Free games are completely excluded. Despite these measures, it is inevitable that unobserved strategies impact pricing.

Second, we looked at a very concrete setting, which limits the generalizability of our results. Community Involvement is a critical success factor for the longevity of products in the PC video game market. However, the success factor "Community" may be less important for other digital platforms, where content consumption involves less interaction with other consumers or producers, such as music and video streaming platforms. Furthermore, long content lifecycles are not of the same relevance for all digital platforms. For news platforms, for example, speed is key while fixed cost are comparably low. Additionally, we also have to be careful about generalizing among PC video games, as we restricted our analysis to the most popular games on Steam due to data quality.

Third, we initially tested the assumptions of Random Effects (see Chapter 5: Model Specification) to be able to estimate the effect of time-invariant game features more easily, however, had to proceed with Fixed Effects. We solved this problem by interacting such variables with time-variant variables to still be able to make statements about price development. Still, it would be worth testing for Random Effects with adapted model specifications (e.g. excluding/including variables) or look into Mixed Models (UCLA, 2020).

Forth, we found that the *Player Number* is negatively associated with price (Model 3). We acknowledge that price and *Player Numbers* may influence each other. When prices are low, for example when discounts are offered, more players are attracted. We identified two solutions to find out more about the causal relationship. First, we could include an instrument variable that has high correlation with *Player Numbers* and low correlation with price to perform a Two Stage OLS. The number of *Twitch Viewers* for each game over time could be suitable. Second, we could lag the variable *Player Numbers* by one month, which gives us an indication of how developers are monetizing a larger player base. In the scope of this paper, we tested Model 3 again without the variable *Player Numbers* to make sure the coefficients of the Community Features were not biased.

Lastly, we have to interpret the results of Model 1 and 2 conservatively, as we do not use Fixed Effects, that absorb any heterogeneity between games. Consequently, there might be unobserved differences between games, e.g. team size or budget, which we cannot account for despite many control variables (omitted variable bias). It would therefore be inappropriate to speak of a clear causal effect of Community Features on price, and more correctly to speak of associations. Additionally, the study assumes that theoretically every game could equally integrate Community Features. However, it is possible that Community Features make less sense for some games, perhaps in the case of story-driven single-player games. At the same time, Community Features may be particularly useful in the context of multiplayer games, which may already have an active, self-sustaining player base, making it inappropriate to attribute positive effects on price to features alone. In reality, therefore, integration is not always decided randomly, but depends on the nature of the game.

8. Conclusion, Implications and Future Research

8.1. Conclusion

In this paper, we set out to answer the question of how Community Involvement influences the price setting of firms on digital platforms. We addressed this question in the context of the gaming platform Steam by looking at three novel ways to promote player interaction and involvement. Specifically, we investigated how pricing of games is influenced by three Community Features that allow players to (1) customize a game with own and peers' game content via the *Workshop* Feature, (2) collect and trade virtual items via the *Tradingcards* Feature, (3) completing challenges and earning social status via the *Achievements* Feature. We showed that games with *Workshop* or *Achievements* demonstrate a higher price level, the latter only at a more advanced age, as well as less price decline over time. Contrary to expectations, we found games with *Tradingcards* to be lower priced and to have stronger price decline, which we explained by the "misuse" of the feature by game developers. With regard to our research question, this predominantly suggest that game developers can charge higher prices for games with Community Features and secondly, that they can delay the natural price decline of their game.

8.2. Implications

Our findings are relevant for game developers. First, they should consider integrating Community Features as a means of maintaining consumer utility and thus willingness to pay in the long run. However, as discussed before (see Chapter 7: Limitations), Community Features do not fit all games - e.g. a multiplayer game may benefit from them differently than a single-player game. The assumption that the mere integration of these features allows to charge higher prices is misguided. Rather, the nature of the game must be taken into account. In the best case, a natural fit between game mechanics and Community Features is already ensured at the conception stage of the game. Secondly, developers who seek a two-way relationship and in particular co-creation with the consumer must be prepared for new time-consuming and costly tasks. They need to respond to customer requests, integrate feedback, provide development tools, create guidelines and ensure compatibility of User Generated Content. Therefore, it is important to consider the trade-off between potentially higher revenue and increased costs of implementing and maintaining Community Features.

Our findings are also important for platform owners. First, we know that the economic success of platforms and content producers is closely linked through revenue sharing. Platforms should therefore think about helping their complementors succeed by empowering them with powerful Community Features that increase the consumer's value. Second, platforms often fight for complementors and consumers according to the "Winner-Takes-It-All" principle. With attractive Community Features, platforms could differentiate themselves in competition with other platforms.

8.3. Future Research

Future research could help generalize our findings for the PC video gaming industry. For example, the sample should be increased and randomized to investigate if our findings apply to games that are less popular. It would also be interesting to investigate the effect of Community Features on the size of the player base of a game over time. In light of growing popularity of alternative monetization strategies, such as recurring revenue through Micro-Transactions, In-App-Purchases, Subscriptions, DLCs, sustaining a loyal player base is essential. Relatedly, it would also be worth looking into the rising phenomenon of free games and their strategies of attracting and monetizing on players. Lastly, it is worth further dissecting the effect of Community Features in inherent utility that's derived regardless of how many others use the features (e.g. customization through own User Generated Content) and network utility that's dependent on how many others use the feature as well (e.g. integration of peers' User Generated Content).

More importantly, we encourage future research of Community Involvement in the context of other novel digital platforms. It will be interesting to see if the new types of Community Involvement we investigated are equally effective in case of media products like music, video and news that have different life-cycles and communities and consumption behavior.

References

Adner, R., & Levinthal, D. (2001). Demand Heterogeneity and Technology Evolution: Implications for Product and Process Innovation. *Management Science*, *47*(5), 611–628.

Baltagi, B. H. (1999). Unequally spaced panel data regressions with AR (1) disturb-ances. *Econometric Theory*, *15*(6), 814–823.

Banks, J. (2013). *Co-creating Videogames*. London: Bloomsbury Publishing.

Barnett, J., & Coulson, M. (2010). Virtually Real: A Psychological Perspective on Massively Multiplayer Online Games. *Review of General Psychology*, *14*(2), 167–179.

Bass, F. M. (1980). The Relationship Between Diffusion Rates, Experience Curves, and Demand Elasticities for Consumer Durable Technological Innovations. *The Journal of Business*, *53*(3), 51–67.

Bass, F. M., & Bultez, A. V. (1982). Technical Note-A Note on Optimal Strategic Pric-ing of Technological Innovations. *Marketing Science*, *1*(4), 371–378.

Benlian, A., Vetter, J., & Hess, T. (2010). Pricing of Content Services-An Empirical Investigation of Music as a Service. In *16th americas conference on information sys-tems.*

Böhm, S., Adam, F., & Farrell, W. C. (2015). Impact of the mobile operating system on smartphone buying decisions: A conjoint-based empirical analysis. In *International conference on mobile web and information systems* (pp. 198–210). Springer Verlag.

Bork, R. H. (1993). *The Antitrust Paradox: A Policy at War with Itself.* New York: Free Press.

Bostan, B. (2009). Player motivations: A psychological perspective. *Computers in Entertainment*, *7*(2), 32.

Bowen Martin, C., & Deuze, M. (2009). The Independent Production of Culture: A Digital Games Case Study. *Games and Culture*, *4*(3), 276–295.

Breusch, T. S., & Pagan, A. R. (1979). A Simple Test for Heteroscedasticity and Ran-dom Coefficient Variation. *Econometrica*, *47*(5), 1287–1294.

Burger-Helmchen, T., & Cohendet, P. (2011). User Communities and Social Software in the Video Game Industry. *Long Range Planning*(5), 44.

Cadin, L., Guérin, F., & Defillippi, R. (2006). HRM Practices in the Video Game In-dustry:. Industry or Country Contingent? *European Management Journal*, *24*(4), 288–298.

Castronova, E. (2005). Synthetic Worlds: The Business and Culture of Online Games. Chicago: University of Chicago Press.

CERI. (2006). *Centre for Educational Research and Innovation.* Paris: OECD Publishing (Schooling for Tomorrow).

Chatterjee, R. (2009). Strategic pricing of new products and services. In *Handbook of pricing research in marketing* (pp. 169–215). Northhampton: Edward Elgar Publishing.

Chatterjee, S., & Hadi, A. S. (1986). Influential Observations, High Leverage Points, and Outliers in Linear Regression. *Statistical Science*, *1*(3), 379–393.

Chesbrough, H. W. (2003). *Open Innovation The New Imperative for Creating and Prof-iting from Technology.* Boston: Harvard Business School Press.

Clarefield. (2018). Gaming Industry: Facts, Figuers and Trends. *Journal of Social Behavior & Personality*.

Claussen, J., Kretschmer, T., & Spengler, T. (2010). *Backward compatibility to sustain market dominance-evidence from the US handheld video game industry.*

Csikszentmihalyi, M. (1990). *FLOW: The Psychology of Optimal Experience.* New York: Harper.

Danet, B., & Katriel, T. (1994). No two alike: play and aesthetics in collecting. In *-terpreting objects and collections. london: Routledge* (pp. 220–239).

Dean, J. (1976). Pricing Policies for New Products. *Harvard Business Review*.

Denny, P. (2013). The effect of virtual achievements on student engagement. In *Conference on Human Factors in Computing Systems - Proceedings* (pp. 763–772).

Dockner, E. J., & Fruchter, G. E. (2004). Dynamic strategic pricing and speed of diffusion. *Journal of Optimization Theory and Applications*, *123*(2), 331–348.

Dolan, R. J., & Jeuland, A. P. (1981). Experience Curves and Dynamic Demand Mod-els: Implications for Optimal Pricing Strategies. *Journal of Marketing. Winter*, *45*(1), 52–62.

Eisenmann, T., Parker, G., & Van Alstyne, M. W. (2006). Strategies for Two-Sided Markets. *Harvard Business Review*.

Farzan, R., & et al. (2008). Results from Deploying a Participation Incentive Mechanism within the Enterprise. In *Sigchi conference on human factors in computing systems.*

Formanek, R. (1994). Why they collect: Collectors reveal their Motivations. In *Inter-preting objects and collections* (pp. 327–335).

Franke, N., & Von Hippel, E. (2002). *Satisfying Heterogeneous User Needs via Inno-vation Toolkits: The Case of Apache Security Software.*

Fruchter, G., & Orbach, Y. (2008). A utility-based dynamic model used to predict ab-normalities in diffusion over time. *Innovative Marketing*, *4*(1), 37–45.

Gallagher, S., & Park, S. H. (2002). Innovation and Competition in Standard-Based Industries: A Historical Analysis of the U.S. Home Video Game Market. *IEEE Trans-actions on Engineering Management*, *49*(1), 67.

Golder, P. N., & Tellis, G. J. (2003). Growing, Growing, Gone: Cascades, Diffusion, and Turning Points in the Product Life Cycle. *Marketing Science*, *23*(2), 207–218.

Gundlach, H., & Hofmann, J. (2017). Preferences and willingness to pay for tablet news apps. *Journal of Media Business Studies*, *14*(4), 257–281.

Guo, Y., & Barnes, S. (2007). Why People Buy Virtual Items in Virtual Worlds with Real Money. In *Data base for advances in information systems* (Vol. 38, pp. 69–76).

Hahsler, M., & Breidert, C. (2006). Adaptive Conjoint Analysis for Pricing Music Downloads. In *Advances in Data Analysis, Proceedings of the 30th Annual Conference of the Gesellschaft für Klassifikation* (pp. 409–416).

Hallford, N., & Lamothe, A. (2001). *Swords and circuitry: A designer's guide to com-puter role-playing games.* Portland: Premier Press.

Hamari, J. (2013). Transforming homo economicus into homo ludens: A field experi-ment on gamification in a utilitarian peer-to-peer trading service. *Electronic Commerce Research and Applications*, *12*(4), 236–245.

Hamari, J., & Eranti, V. (2011). Framework for Designing and Evaluating Game Achievements. In *Digra 2011 conference: Think design play.*

Hamari, J., & Koivisto, J. (2013). Social motivations to use gamification: an empirical study of gamifying exercise. In *21st european conference on information systems.*

Hamari, J., & Lehdonvirta, V. (2010). Game design as marketing: How game mechan-ics create demand for virtual goods. *Journal of Business Science and Applied Management*, *5*(1), 14–29.

Hausman, J. A. (1978). Specification Tests in Econometrics. *Econometrica*, *46*(6), 1251–1271.

Humphreys, S. (2005). Productive users, intellectual property and governance: the chal-lenges of computer games. *Media and Arts Law Review*, *10*(4), 299–310.

Jakobsson, M. (2011). The Achievement Machine: Understanding Xbox 360 Achieve-ments in Gaming Practices. *The International Journal of Computer Game Research*, *11*(1), 1–22.

Jakobsson, M. (2016). *'Achievements', in Debugging Game History: A Critical Lexicon.* Boston: MIT Press.

Jeppesen, L. B. (2004). *Profiting from innovative user communities: How firms organize the production of user modifications in the computer games industry.*

Jeppesen, L. B. (2005). User Toolkits for Innovation: Consumers Support Each Other. *Journal of Product Innovation Management*, *22*(4), 347–362.

Jöckel, S., Will, A., & Schwarzer, F. (2008). Participatory Media Culture and Digital Online Distribution-Reconfiguring the Value Chain in the Computer Game Industry. *International Journal on Media Management*, *10*(3), 102–111.

Jung, J. H., Schneider, C., & Valacich, J. (2010). Enhancing the Motivational Af-fordance of Information Systems: The Effects of Real-Time Performance Feedback and Goal Setting in Group Collaboration Environments. *Management Science*, *56*(4), 724–742.

Juul, J. (2010). *A casual revolution: Reinventing video games and their players.* Boston: MIT press.

Kalish, S. (1983). Monopolist Pricing with Dynamic Demand and Production Cost. *Source: Marketing Science*, *2*(2), 135–159.

Katz, M. L., & Shapiro, C. (1985). Network Externalities, Competition, and Compatibility. *The American Economic Review*, *75*(3), 424–440.

Koch, S., & Bierbamer, M. (2016). Opening your Product: Impact of User Innovations and their Distribution Platform on Video Game Success. *Electronic Markets*, *26*(4), 357–368.

Koch, S., & Kerschbaum, M. (2014). Joining a Smartphone Ecosystem: Application Developers' Motivations and Decision Criteria. *Information and Software Technology*, *56*(11), 1423–1435.

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

Landsman, V. and Stremersch, S. (2011). Multihoming in Two-Sided Markets: An Empirical Inquiry in the Video Game Console Industry. *Journal of Marketing*, *75*(6), 39–54.

Lastowka, G. (2007). User-Generated Content and Virtual Worlds. *Vanderbilt Journal of Entertainment and Technology Law*, *10*(1), 893–912.

Leibovitz, L. (2013). Atari Bankrupt: Video Game Industry Refuses to Heed History. *The New Republic*.

Lerner, J., & Triole, J. (2002). The Simple Economics of Open Source. *Journal of Industrial Economics*, *52*(1), 197–234.

Levitt, T. (1965). Exploit the Product Life Cycle. *Harvard Business Review*.

Lilien, G., & et al. (2001). Performance Assessment of the Lead User Idea Generation Pro-cess for New Product Development. *Management Science*, *48*(8), 1054–1059.

Lin, D., Bezemer, C. P., & Hassan, A. E. (2018). An empirical study of early access games on the Steam platform. *Empirical Software Engineering*, *23*(2), 771–799.

Liu, H. (2010). Dynamics of Pricing in the Video Game Console Market: Skimming or Penetration? *Journal of Marketing Research*, *47*(3), 428–443.

Locke, E. A., & Latham, G. P. (1991). A Theory of Goal Setting and Task Performance. *The Academy of Management Review. The Academy of Management*, *16*(2), 212–247.

Locke, E. A., & Latham, G. P. (2002). Building a Practically Useful Theory of Goal Setting and Task Motivation A 35-Year Odyssey. *American Psychologist. American Psychological Association Inc*, *57*(9), 705–717.

Luthans, F., & Stajkovic, A. D. (1999). Reinforce for Performance: The Need to go Beyond Pay and even Rewards. *The Academy of Management Executive*, *13*(2), 49–57.

Marchand, A. (2016). The power of an installed base to combat lifecycle decline: The case of video games. *International Journal of Research in Marketing*, *33*(1), 140–154.

Mekler, E. D., Brühlmann, F., Opwis, K., & Tuch, A. (2013). *Do Points, Levels and Leaderboards Harm Intrinsic Motiva-tion? An Empirical Analysis of Common Gamification Elements.* Ontario.

Meyer, T. G. (2012). *Path Dependence in Two-Sided Markets.*

Montola, M., Nummenmaa, T., Lucero, A., Boberg, M., & Korhonen, H. (2009). Applying Game Achievement Systems to Enhance User Experience in a Photo Sharing Service. In *13th international academic mindtrek conference: Everyday life in the ubiquitous era* (pp. 94–97).

Nair, H. (2004). Intertemporal Price Discrimination with Forward-Looking Consumers: Application to the US Market for Console Video-Games. *Quantitative Marketing and Economics*, *5*(3), 239–292.

Nikou, S., & et al. (2014). A Consumer Perspective on Mobile Service Platforms: A Con-joint Analysis Approach. *Communications of the Association for Information Systems*, *34*(1), 1409–1424.

Osborne, J. (2010). Improving your data transformations. *Practical Assessment*, *15*(1), 12.

Park, B. W., & Lee, K. C. (2011). Exploring the value of purchasing online game items. *Computers in Human Behavior*, *27*(6), 2178–2185.

Park, M. (2010). Defying Obsolescence. In *Longer lasting products: Alternatives to the throwaway society* (p. 77). Vermont: Gower Publishing.

Parmentier, G., & Gandia, R. (2013). Managing Sustainable Innovation with a User Community Toolkit: The Case of the Video Game Trackmania. *Creativity and Innova-tion Management*, *22*(2), 195–208.

PC Gamer. (2019). *Valve removed 1000 games from Steam because publishers were 'abusing' Steamworks.* Retrieved 2020-06-14, from https://www.pcgamer.com/uk/1000-games-were-just-removed-from-steam-and-we-dont-know-why/

Poor, N. (2014). Computer game modders' motivations and sense of community: A mixed-methods approach. *New Media & Society*, *16*(8), 1249–1267.

PwC. (2017). *Global Entertainment and Media Outlook 2017.* Retrieved from www.pwc.com/outlook

PwC. (2019). *Global Entertainment and Media Outlook 2019.* Retrieved from https://www.pwc.com/gx/en/entertainment-media/outlook-2019/entertainment-and-media-outlook-perspectives-2019-2023.pdf

Reddit. (2019). *Steam is removing hundreds of games from the store.* Retrieved 2020-06-14, from https://www.reddit.com/r/Steam/comments/e1obe3/steam_is_removing_hundreds_of_games_from_the/

Rietveld, J., & Eggers, J. P. (2018). Demand Heterogeneity in Platform Markets: Implications for Complementors. *Organization Science*, *29*(2), 304–322.

Roberts, J. H., & Lilien, G. L. (1993). Explanatory and Predictive Models of Consumer Behavior. *Handbooks in Operations Research and Management Science*, *5*(1).

Rozin, P. (2000). Preadaptation and the puzzles and properties of pleasure. *Well-being: The foundations of hedonic psychology*, 109–133.

Scharkow, M. e. a. (2015). Beyond the "core-gamer": Genre preferences and gratifications in computer games. *Computers in Human Behavior*, *44*(1), 293–298.

Schreier, M. e. a. (2007). Lead users and the adoption and diffusion of new products: Insights from two extreme sports communities. *Marketing Letters*, *18*(2), 15–30.

Shy, O. (2001). The Economics of Network Industries. *Cambridge University Press*.

Shy, O. (2011). A Short Survey of Network Economics. *Review of Industrial Organization*, *38*(2), 119–149.

Steam. (2020a). *Features (Steamworks Documentation).* Retrieved 2020-06-08, from https://partner.steamgames.com/doc/features

Steam. (2020b). *Steam Community: Steam Trading Cards.* Retrieved from https://steamcommunity.com/tradingcards/

Steam. (2020c). *Steam Direct Product Submission Fee on Steam.* Retrieved 2020-06-09, from https://store.steampowered.com/sub/163632

Steam. (2020d). *Steam Subscriber Agreement.* Retrieved 2020-06-21, from https://store.steampowered.com/subscriber_agreement/?l=english

Steam Blog. (2015). *Steam Blog: Mods on Steam.* Retrieved 2020-06-21, from https://store.steampowered.com/about/communitymods/?l=english

Steam Blog. (2017). *Changes to Trading Cards.* Retrieved 2020-06-14, from https://steamcommunity.com/games/593110/announcements/detail/1954971077935370845

Steam Blog. (2020). *Steam Blog: Removing Payment Feature Skyrim Workshop.* Retrieved 2020-06-21, from https://steamcommunity.com/games/SteamWorkshop/announcements/detail/208632365253244218

Steam Card Exchange. (2020). *Steam Card Exchange: Games with Tradingcards.* Retrieved 2020-06-22, from https://www.steamcardexchange.net/index.php?showcase

Steamspy. (2020). *Monthly summaries - SteamSpy - All the data and stats about Steam games.* Retrieved 2020-06-07, from https://steamspy.com/year/

Tabachnick, B. G., & Fidell, L. S. (2007). Using Multivariate Statistics (5th Edition). *Pearson Education*.

Thom, J., Millen, D., & DiMicco, J. (2012). Removing gamification from an enterprise SNS. *Proceedings of the ACM Conference on Computer Supported Cooperative Work*, 1067–1070.

UCLA. (2020). *Introduction to Linear Mixed Models.* Retrieved 2020-06-24, from https://stats.idre.ucla.edu/other/mult-pkg/introduction-to-linear-mixed-models

Urban, G. L., & Von Hippel, E. (1988). Lead user analyses for the development of new industrial products. *Management Science*, *34*(5), 569–582.

Varian, H. (1992). *Microeconomic Analysis*. WW Norton & Company.

Von Hippel, E. (1986). Lead Users: A Source of Novel Product Consepts. *Management Science*, *32*(7), 791–805.

Von Hippel, E., & Katz, R. (2002). *Shifting Innovation To Users Via Toolkits* (Vol. 4232).

Wang, H., & Sun, C. T. (2011). Game Reward Systems: Gaming Experiences and Social Meanings. In *Digra 2011 conference.* Atlanta.

Weerahandi, S., & Dalal, S. R. (1992). A Choice-Based Approach to the Diffusion of a Service: Forecasting Fax Penetration by Market Segments. *Marketing Science. Winter*, *11*(1), 39–53.

Whang, L. S. M., & Kim, J. Y. (2005). The Comparison of Online Game Experiences by Players in Games of Lineage & EverQuest: Role play vs. Consumption. In *DiGRA 2005 Conference: Changing Views - Worlds in Play*. Vancouver.

White, H. (1980). A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica*, *48*(4), 817–838.

Yee, N. (2006). Motivations for Play in Online Games. *CYBERPSYCHOLOGY & BEHAVIOR*, *9*(6), 772–777.

Yusuf Dauda, S., & Lee, J. (2015). Technology adoption: A conjoint analysis of con-sumers' preference on future online banking services. *Information Systems*, *53*(1), 1–15.