# When is the best time to enter a subscription platform?

Analysis of the game subscription platform entry strategies from the perspective of the game developers

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# Abstract

In this research, I provide a novel approach to the software developer entry strategy studies by studying the potential launch strategies into subscription platform markets. It is not only significant for the game developer to decide whether they are willing to launch their game on the subscription platform, but even more importantly when to release it. Theory shows that early releases can generate positive advertising effects, informing new audiences about the title and providing them with the opportunity to test it with zero marginal costs. I show in my research that this strategy is especially applicable for indie developers with games that are not part of a franchise, as they can leverage the advertising potential the most. Furthermore, I reveal that the superstar and medium-budget games on average launch later on the subscription platforms, and their launch performance counted as the review density is weaker during the subscription entry compared to the official release. In the end, I create a predictive model for the optimal entry strategy. The results are presented as the Individual Conditional Expectation plots for the launch performance variable for different configurations of the features, which can be leveraged by the managers to find the optimal launch timing given their software's characteristics.

# Introduction

PC and console game developers have been mostly using two main channels to distribute and sell their products: psychical and digital, with the latter one reaching 89.5% of overall game sales in 2022 in the UK (Digital Entertainment and Retail Association 2022), while in the US only 10.3% of the newly released titles were available in the physical form (the NDP Group 2022). This trend illustrates that currently most of the games are being sold in a digital way, which has opened a space for the development of more innovative forms of online game distribution. These new forms range all the way from offering free-to-play games with in-game purchases (Rearick 2023), enabling access to the game for a monthly subscription (Rodríguez 2022), to selling virtual goods and game expansions (Thomas 2022), which allows game developers to create more value from their product. However, they all have one major downside to the final consumer – they offer just access to one single title. That problem is being solved with the inception of game subscription platforms.

The idea of creating a subscription platform similar to Spotify or Netflix but implemented in the gaming industry was already proposed by researchers at the beginning of the last decade (Marchand and Turao 2013). The idea was to offer customers access to a full library of games for a fixed monthly fee. One of the first major players on this market was Microsoft with the release of Xbox Game Pass in 2017. It was soon followed by Sony, which released its own platform named PlayStation Plus. The main motivation from the perspective of the game developers to offer their games on such platform is the possibility of earning constant monthly income from the subscription, in contrast to the traditional model in which they are forced to make multi-million bets with the development of each new title to only be able to cash it in during the first few months after the release. However, the profitability of this strategy is difficult to study, as the financial data about the performance of the particular titles are usually not disclosed by the companies, rather the only available data is on the overall platform level (Makuch 2022). Yet, the indicator that can be measured is the popularity of the game, proxied by the number of reviews and their content.

Therefore, in this paper I will aim to study the effectiveness of game launches on the subscription platform from the developer's perspective, which will be measured by the dynamics of popularity of the game observed after the platform launch. Furthermore, I will check the impact of launch timing and game category on the post-launch popularity of the game.

I will model it by comparing the popularity of the game before and after its release on the platform. I will also look at the trends in the reviews of those games to see, if and to what extent the launch on the subscription platform affects the perception of those games by the users. In the end, I will aim to answer the question about finding the most appropriate timing for the release of the software on the game subscription platform maximizing the post-launch popularity.

The explanatory research will enable software developers to assess the opportunities of the subscription platform release given the characteristics of their game. Then they will be able to decide on their launch strategy on the subscription platform by leveraging the results of the predictive research.

The strategy for releasing new titles on the subscription platform differs depending on the game developer. The gaming studios owned by Microsoft release their games on the Xbox Game Pass platform immediately after global release, even in the case of the most demanding AAA titles (as with the Forza Horizon 5 release). Because of this strategy many of the newest titles become instant blockbusters, partly thanks to the immediate access to the substantial userbase provided by the subscription platform (Taylor-Hill 2023). This strategy also allows Microsoft, as the owner of the subscription platform, to keep its users entertained with the newest titles, making use of the indirect network effects between the fresh software available on the platform and the purchases of the memberships.

Other gaming studios release their titles with some delay, which ranges from a few months (FIFA 22 release) to even a few years (Far Cry 5 release). Those strategies usually depend on the penetration phase of the price discrimination strategies implemented by developers and are allowing them to gather more profit in more advanced stages in the product lifetime. It also shows that the time of the release is critical for the success of a game in the subscription model. An early platform launch creates a risk of customer anticipation of the future availability on the subscription platform leading to sales cannibalization, while a late launch may lead to little interest from the players in the game. This shows that a detailed study of the effectiveness of subscription platform game launches is needed to understand the potential of game developers in this market and to provide them with real-life managerial insights.

The novelty of my research topic imposes some limitations in terms of the academic literature review, as the game subscription platforms operate in a different revenue model than the classic ones. Nevertheless, the two-sided rules still apply to them, and the indirect network effects can also be observed.

The main difference between those two types of platforms is the revenue distribution. On the classic game distribution platforms game developers receive a margin for each unit sold, whereas in the case of subscription platforms there is a variety of revenue models. As stated by Ed Fries, the former executive of Xbox Game Pass, the revenue model for the developers of Game Pass titles is not homogenous and strongly depends on the type of game developer. Usually, small independent studios prefer the one-off payment for launching the game on the platform, while the major game developers choose usage-based payments or fixed monthly fee models.

Those differences in the revenue models are crucial for subscription platforms and prevent me from immediately generalizing all of the theories applicable to the gaming industry to the subscription platforms market. Therefore, my contribution to the literature will be the assessment of the relevance of indirect network effect and price discrimination theories.

## Literature Review

In the domain of video games, most of the relevant literature focuses on indirect network effects and the two-sided nature of the gaming industry, illustrating the synergies in the concurrent growth of hardware and software sales. Therefore, to maintain the broader context, this literature review will first introduce current research on platforms and then focus on the software side, studying both the launch strategies of games and the game positioning of developers. I will explain the most relevant drivers of software sales on platforms, such as installed base, superstar games and general game variety among others. After that, in order to be able to correctly assess the effectiveness of subscription platform software launches, I will review the marketing literature on subscriptions, searching for theories that would explain the rationale behind different launch strategies, including but not limited to price discrimination theory.

By marrying these two streams of research, I will aim to contribute to the literature by studying the benefits of software launches on subscription platforms from the perspective of game developers. Measuring the impact of the subscription service on the game popularity, I provide novel insights into the gaming platform literature, which is currently dominated by papers using more traditional performance measures as sales data.

It is highlighted by many researchers that the gaming industry behaves like a typical two-sided market (Landsman and Stremersch 2011, Allen and Gretz 2022, Stremersch and Tellis 2007), with game developers acting as sellers and players acting as buyers on the game distribution platforms. The same can be said about the game subscription platforms. This gives rise to direct and indirect network effects, which happen in parallel producing a net outcome of both. Allen and Gretz (2022) explain these effects using the example of a new game launch on a platform, denoting that an immediate direct network effect is sales cannibalization because customers tend to choose the new titles over the older ones. After that, the indirect network effect can be observed as the new titles attract more customers to the platform expanding the userbase of the platform, hence also bringing new players to the other games on this platform. However, Landsman and Stremersch (2011) point out that the strength of this effect is dependent on the platform exclusivity of particular software, leading to a much lower impact on other game sales in the case of multi-platform titles. Rysman (2009) further challenges the definition of indirect network effects, suggesting that the two-sidedness of the market which is obligatory for the indirect network effects to occur is only viable when the developers have a share in the usage-based revenue of their software (in contrast to the revenue model in which they receive a one-off payment for the rights to their software). In fact, this assumption can also be applied to the subscription platform market, as a majority of game developers base their contracts on the usage of their software benefitting from the indirect network effects of the overall platform adoption growth (Batchelor 2020).

Academics outline that the overall strength of the indirect network effects on the platform is dependent on the several features of the software portfolio (Stremersch et al. 2007, Sun et al. 2015). Stremersch et al. (2007) explain that the overall software availability affects the strength of the network effects, stating that the volume of the different titles leads to an increase in this aspect. Zhu et al. (2012) challenge this view by proving, that it is the overall variety of the software rather than its pure volume that boosts the appearance of the mutual indirect network effects. They suggest that customers seek variety in the platform markets, amplifying the relevance of the software genre on its attractiveness. This applies also to gaming subscription platforms, with Xbox highlighting the uniqueness of each game in their library as the unique selling point of their offer (Castillo 2023).

Although the theory on the platform markets and their behavior is important to my topic, even more crucial is the literature coverage on the drivers of particular software sales. Academics agree that the game quality often depicts the sales potential of software (Binken et al. 2009, Cox 2014, Malshe et al. 2019, Kim et al. 2014). The titles with the highest budget and superior quality are often referred to as superstar games. Binken et al. (2009) and Cox (2014) denote that not only can the superstar titles achieve substantial sales values after the launch, but they also have a major impact on hardware adoption. This research is further replicated and developed by Malshe et al. (2019) who finds that superstar titles enjoy a particularly large demand during the early stages of the platform's lifetime. Kim et al. (2014) attempt to generalize this theory by stating, that the game quality in general has a strong positive impact on both its sales and the overall platform adoption, which in turn implies increased sales of the other titles on the platform, including the lower quality ones.

Launch strategies and price discrimination is yet another factor that impacts software sales. Companies realize that customers are willing to pay a premium for early access to a game, which creates higher margins at the beginning of a product's lifetime (Nair 2007). After that in the more mature stages, game developers are in need to discount their products in order to attract more users. Here, Nair highlights the fact of consumer forward-looking behavior which entices many potential early adopters of software to postpone their purchase in the motivation to save money. In fact, most scholars in their price discrimination studies point out that assessing the actual forward-looking behavior of customers is one of the most important success factors of a price strategy in the durable goods market (Aviv and Pazgal 2008, Balachander and Srinivasan 1998, Liu 2010). This theory will be further extended in the Conceptual Framework.

# Conceptual Framework

In order to link my findings with the extant literature, I provide a thorough analysis of the two marketing theories whose mechanisms can be observed in the subscription platform industry. Those theories are the price discrimination on the durable goods market, which motivates developers to enter subscription platforms in the mature stages of the software lifetime and the advertising theory, which explains why some developers decide to launch their title on the day one leveraging the immediate access to the extensive userbase of the platform.

Then, I analyze the outcome of the theory overview and the literature review in order to find the key variables that will be further used in the model. Here I introduce both the variables used in the previous research as well as the new variables that I deem relevant to the gaming subscription platform topic. In the end, I introduce the hypotheses that I expect regarding my research.

## Price Discrimination in the durable-goods market

The video games market can be perceived as an example of a durable goods market, as games do not own a tendency to wear out over time. The durability of games implies certain characteristics on the market. Firstly, once a consumer purchases a game, he automatically exits from the product market of this game in the subsequent periods (Rysman et al. 2012), which enforces a shrinking nature upon the client base of the gaming industry. Secondly, consumers choose their individual moment of purchase based on their own perceived valuation of the game, introducing the decreasing overall average valuation of the game with the growth in the number of customers exits (Nair 2007). This would imply that the game developers should steadily decrease their prices in time, compensating for this decrease in the average valuation.

However, the consumers in the durable goods market form their future price expectations, which leads them to differ in their purchases. Game developers need to take this into account when developing their pricing strategies. Scholars enlist a few main drivers of the forward-looking behavior of the customers in such a market. Nair (2007) claims that the main incentive to delay a purchase moment of a game is the rationality of customers, who are able to anticipate future prices. Therefore, the strength of this driver is the function of consumer expectations about the future prices of the game, which are derived from the prices chosen by the firm. Rysman et al. (2012) add that consumers anticipate not only future price declines but also quality improvements, which leads them to delay their purchases. Other academics synthesize the arguments mentioned before, claiming that the customers try to predict the perceived experience curve of a company producing this durable product in the search for an optimal moment of purchase (Balachander et al. 1998).

In order to maximize the potential future profits, game developers need to find an equilibrium in their pricing strategy accounting for customers' forward-looking behavior. In general, this equilibrium is found in the literature by calculating the optimal sequence of prices considering the discount factors of both the company and the customers (Besanko et al. 1990). However, in my research I will try to find the most accurate timeframe in the software lifetime to launch it on the subscription platform in order to maximize the popularity dynamics related to this launch. This is also dependent on the forward-looking behavior of the consumers, although this time they differ their current purchase moment to wait for the game release on the subscription platform, which enforces some differences in the rules occurring on the market.

Firstly, customers who currently own a subscription on the platform do not commit any additional cost to own a new game, although they need to maintain their subscription throughout the entire period of their planned gameplay. That is mainly based on their perceived willingness to pay for the content (Wang et al. 2005). Secondly, instead of classic per-unit-sold revenue, game developers can enjoy a variety of different revenue models, enabling them to discount the potential future revenues on the platform by receiving advance payment for the game launch. Hence, a strategically thinking game developer will enter the subscription platform at the moment when the overall value of the discounted future profits generated by the title on the platform will surpass the value of the forgone income the software would generate from other sources if it was not available on the platform.

This lost income is related to the value of additional sales in classic distribution which would be generated if the game was not launched on the subscription platform. It needs to be acknowledged, that this lost value is very difficult to measure, as the subscription platform entry allows developers to introduce a price discrimination mechanism between price-intensive and price-sensitive buyers at the same point in time.

## Advertising theory

The aforementioned marketing theory suggests that a strategically thinking developer should wait for the launch on the subscription platforms until it becomes economically beneficial, however this theory does not explain why numerous games are released on those platforms on the day one of their official release. That suggests that there is yet another factor that software producers take into consideration when evaluating a decision on the date of launch – the promotional effect of the platform launch.

It is very important to acknowledge the advertising potential of the subscription platform which motivates many small developers to release their games on such platforms. Many researchers highlight that customers search for information about the product before purchase to reduce their uncertainty about it (Moorthy et al. 1997, Murray 1991). That is why sellers should actively attempt to increase the exposure of their product to potential clients, either to directly influence the sales or to indirectly impact it by increasing word of mouth (Bloch et al. 1986). Moreover, Guitart and Stremersch (2021) find that informative advertising and online search increase have a stronger impact on the lower priced products, which can also be applied to the case of small developers.

According to advertising theory, the effectiveness of advertising can be attributed to its ability to inform and persuade (Ackerberg 2001, Mehta et al. 2008). Advertising informs consumers by providing product information that reduces uncertainty about the product's true quality. Additionally, advertising persuades consumers by creating associations with certain images that give the product social meaning and emotional value. The informative aspect of advertising relies on informational content, which emphasizes factual information or the practical consequences of using the product. Bagozzi et al. (1999) and Puto et al. (1984) define this as content that provides useful information. On the other hand, the persuasive aspect of advertising relies on emotional content, which either evokes emotions or communicates intangible value and emotional benefits that consumers will experience through owning or using the product. Researchers define this as content that taps into consumers' emotions and expresses value and pleasure.

As small developers usually have scarce marketing resources it is not surprising that they are potentially the biggest beneficiaries of the inform and persuade factors that subscription platform brings. These developers also tend to leverage the platform’s user base to have immediate access after launch to the vast number of potential players as well as to put the majority of the promotion efforts onto the platform owner. Lee et al. (2003) explain that the extensive installed base is one of the most important factors that attract new software to the platform, even if the platform has inferior technology. That is especially relevant for small developers with relatively innovative software, as subscription platform users are more likely to try them out in oppose to more conservative, classic video game consumers (Rietveld et al. 2018).

Another factor that makes early launches a good strategy for small developers is instant cash flow, as the contract with small developers usually relies on the one-off payment of the production costs with a premium (Batchelor 2020).

## Relevant variables

I will begin my research with the explanatory model, in which I will aim to describe the relationships between the focal and outcome variables and try to uncover the underlying trends. Then, I will use those findings to predict the best launch strategy on the subscription platform given the set of game characteristics.

In the explanatory model, I will compare the pre-and post-launch review sets of games that were released on the subscription platforms looking both at their content as well as their overall count and density (reviews per month). The main purpose will be to find the most common themes that were presented in both review sets and to measure the shift in those themes and their sentiments after the moment of the subscription platform launch. Above that, I will measure the appearance and the strength of the post-launch popularity increase of the game by looking at the count and density of reviews in both subsets.

In this model, I will be using the set of focal and outcome variables. The explanatory variable will be the subscription platform boolean, indicating whether the particular review was added during the period when the game was available on the subscription platform, or it was outside of this period. The information stored in this variable is of fundamental meaning to my research as my main target is to study and describe the differences in software performance before and after release on the subscription platform.

Moreover, I will extend my research by introducing several focal variables, which will be particularly useful in deriving group-specific insights for particular game categories. The first focal variable is the budget category, which will distinguish between superstar titles, low-budget indie games and others. This indicator was previously used by several academics in their research models, with all of them agreeing that the software production budget and quality are key differentiators in the gaming market, which I have shown in the literature review. It also complies with the aforementioned advertising theory, suggesting that high- and low-budget game developers tend to have different motivations when reviewing their subscription platform launch strategies. The advertising theory suggests, that the less-known, low-budget games have stronger needs to inform and persuade people, therefore making it better for subscription platform launches. The additional positive effect of subscription entry on market reach will thus be higher, especially when entering soon, as information is especially effective in the early product lifecycle stage. We can therefore suspect that niche software will enter sooner and benefit more from entering sooner.

Next variable is the availability of in-game purchases, the additional content that users can buy when owning the game. Games with such options available can generate additional income per player, also including users of the subscription platform. Therefore, based on the price discrimination theory we should expect those games to enter the platform earlier, as the potential revenue generated by the platform users is higher. In fact, Microsoft (2022) claims that their Game Pass users on average spend 50% more on in-game content than non-Game Pass users.

Another focal variable is the game genre, which also is commonly used throughout multiple academic research on gaming topics. As mentioned in the literature review, the number and distribution of different genres can work as a proxy of the platform game variety. Academics suggest that games in the genres with lower coverage can enjoy relatively higher interest as they have weak direct competition. I also expect those titles to benefit from stronger advertising effects driven by better positions in their less-occupied genre.

I will also look at whether the game is exclusive to the single platform or if it can be also available on different hardware options. Many academics suggest that single homing of the software is especially beneficial from the perspective of the platform owner, as it leads to an increase of indirect network effects following the game release. On the other hand, games that are multi-homed can reach a broader audience thanks to their better availability.

In my model, I will also study the franchising of the software, as it is common for games to be released in the series. I would expect those games to be released on subscription platforms relatively later as they need less advertising efforts for each new iteration. I also expect franchised games to have similar popularity performances inside the series, as they tend to boost each other’s performance and popularity.

The main outcome variable which I will be using in my model will be the game reviews added by the platform users, including its content, count and position in time. It will allow me to study the shifts in popularity before and after the subscription platform launch as well as to study the relationship between the topics and the focal variables. Above that I will study the sentiment of the reviews and look at the review ratings to broaden my picture of different game subgroups defined based on their features.

The next outcome variable, which will be also implemented in the predictive model is the timing of the release on the subscription platform relative to its official launch. I will use it to distinguish different entry strategies and find dependencies between focal variables and the best launch strategy.

In the second part of my research, I will use the findings from the explanatory research to create a predictive model which will aim to find the best subscription platform entry timing based on the software characteristics.

# Data

## Empirical Setting

In my research, I will be studying the impact of the subscription entry of a game. The gaming subscription industry is rather young, with major players such as Microsoft and PlayStation establishing their position in this market only a few years ago. The whole idea beneath the gaming subscription platform concept is rather similar to other entertainment subscription services – users in return for the fixed monthly fee gain access to the extensive game library which they can download and play for free. It is worth noting, that if a particular game exits from the platform offering or in case the user cancels its subscription, he immediately loses access to the downloaded content.

The first major gaming subscription platform was launched in 2017 by Microsoft and was called Xbox Game Pass. It was followed by Sony with the revamp of their Play Station Plus service which from 2022 has been operating in a similar business model to its Xbox competitor. Both of the subscription platforms offer tiers with different offerings depending on the price paid, however as in the Xbox Game Pass all of the subscribers get access to the same library of games, and the offering composition of Play Station Plus is more complex. The basic subscribers only get access to a small number of monthly rotating titles with the key selling point of this subscription being access to the online multiplayer capability of the console. Only the higher tier subscribers get access to the larger game library comparable to the Xbox offering making them the most accurate competitor of the Game Pass service.

Xbox Game Pass has gone on to become a major success for Microsoft, gathering over 10 million subscribers by 2020 and 25 million by 2022. For Play Station Plus this number reached 50 million in May 2023, however the number of higher tier subscribers formed only 30% of the overall subscriber base.

As the composition of the platform’s library depends not only on the platform owner but mostly on the decision of the game developers, it is essential to study the impact of the subscription entry on the developer and find potential drivers that motivate them to launch their product on such platform. This question is not only relevant for the gaming subscription industry but also for other software subscription services and therefore the findings can be generalized to those markets as well (accounting for the potential structural differences).

## Sample and Data Collection

In my model, I will use the data composed of the Xbox Store user reviews of different PC games available on the Xbox Game Pass. I decided to limit my data sample only to this platform as its competitor Play Station Plus offering its services through Play Station Store does not have an option to leave a game review.

To gather the data, I scraped the user reviews of all of the titles available on Game Pass on PC on June 15, 2023, from the US version of the Xbox Store, which resulted in 243,806 reviews of 352 different games. For each review, I extracted the content, rating and the date of the review followed by the detailed features of the game, including its official release date, its developer and publisher, age category, genre and the official price at launch. Then, I manually searched for the date of the first launch on Game Pass for each game by reading the official news articles and releases regarding the new titles added to the Xbox Game Pass portfolio. In the last step, I manually filled in the data for other relevant variables by attributing each game with a budget category based on the news articles and reported production budget, a franchise category based on the existence of other games in the series, the availability of the in-game purchases and exclusivity of a game by looking whether a title is only available on PC, only for Microsoft (PC and Xbox) or whether it is multi universally playable.

## Variable Operationalization

| | Variable Name | Definition |
|---|---|---|
| Review-related | Review Content | The written content of the review including the punctuation and emoticons |
| | Review Rating | The rating attributed by the reviewer ranging from 1 to 5 stars, without decimal points |
| | IsAfterGP | Dummy variable that equals 1 if the review was posted after the game entered the subscription service, and 0 otherwise |
| | Phase | Phase in the lifetime of a title when the review was posted (more on this in the review density analysis) |
| Game-related | Official Release | Date when the game was officially released on the Xbox Store |
| | Game Pass Release | Date of the launch of the game in the Game Pass library |
| | Budget Category | Budget category of the game (indie, medium budget or superstar) |
| | Franchise | Indicator whether the game is a part of the franchise |
| | Exclusivity | Indicator whether the game is exclusive to PC, to Microsoft (PC + Xbox) or is universally available |
| | In-game purchases | Indicator whether the game enables users to purchase additional in-game content |
| | Genre | Genre of the game (each game can be attributed to multiple genres) |

*Figure 1: Select variable names and definitions*

## Summary Statistics

| Data | All | | Left for analysis | | Filtered ot during cleaning | |
|---|---|---|---|---|---|---|
| Number of reviews | 243,806 | | 176,470 | | 67,336 | |
| Number of Games | 352 | | 350 | | 2 | |
| **Review time** | Before Game Pass Launch | | | After Game Pass Launch | | |
| Number of reviews | 49,758 | | | 126,712 | | |
| **Budget Category** | Indie | | Medium Budget | | Superstar | |
| Number of reviews | 52,892 | | 35,148 | | 88,430 | |
| Number of Games | 130 | | 95 | | 125 | |
| **Entry timing** | Day One | < 1 month | < 6 months | < 12 months | < 24 months | > 24 months |
| Number of reviews | 84,526 | 4,494 | 8,090 | 14,875 | 18,050 | 46,435 |
| Number of Games | 194 | 9 | 16 | 30 | 30 | 71 |
| **Franchise** | Yes | | | No | | |
| Number of reviews | 82,135 | | | 94,335 | | |
| Number of Games | 177 | | | 173 | | |
| **In-game purchase** | Yes | | | No | | |
| Number of reviews | 94,303 | | | 82,167 | | |
| Number of Games | 142 | | | 208 | | |
| **Exclusivity** | PC | | Microsoft | | No | |
| Number of reviews | 4,962 | | 33,545 | | 137,963 | |
| Number of Games | 26 | | 46 | | 278 | |
| **Genre Category** | Common | | | Uncommon | | |
| Number of reviews | 69,816 | | | 106,654 | | |
| Number of Games | 186 | | | 164 | | |
| **Review Rating** | 1 | 2 | 3 | 4 | 5 | Av. Rating |
| Number of reviews | 51,667 | 17,934 | 17,299 | 22,415 | 67,155 | 3.2 |

| Game Genre | Number of Games | % of all Games |
|---|---|---|
| Action & adventure | 185 | 53% |
| Role playing | 77 | 22% |
| Shooter | 72 | 20% |
| Simulation | 69 | 20% |
| Strategy | 48 | 14% |
| Platformer | 25 | 7% |
| Family & kids | 22 | 6% |
| Sports | 21 | 6% |
| Other | 19 | 5% |
| Puzzle & trivia | 16 | 5% |
| Racing & flying | 16 | 5% |
| Fighting | 13 | 4% |
| Classics | 6 | 2% |
| Card & board | 4 | 1% |
| Word | 3 | 1% |
| Music | 2 | 1% |
| Tools | 1 | 0% |
| Multi-Player Online Battle Arena | 1 | 0% |

*Figure 2: Main summary statistics of the dataset*

Figure 2 presents the summary statistics of the dataset using both the number of reviews and games. The dataset is stable and representative, featuring good distribution between categories in different control variables. That is important for further research, as samples with too little representation could deem unreliable results. During the data cleaning, I left out 67,336 reviews that were either too short (under 5 words), not in English, or were duplicates of other reviews in the dataset. That resulted in the final set of 176,470 reviews from 350 different Game Pass games.

The source of most of the variables and their derivation was already discussed in the data collection part. The two custom variables which were created based on the other data points are the Entry Timing and the Genre Category. The first one attributes the entry timing category based on the length of the time window between the official release and the launch of the Game Pass. Note that those categories are not cumulative, meaning that the < 6 months category represents games that launched on Game Pass more than 1 and less than 6 months after the official release.

To create the Genre Category I first created a genre table to see the popularity of each genre (those values do not sum up to 100% as each game can have multiple genres). Then I set the cutoff point at 15% in order to distinguish between the common and uncommon game genres. This allows me to test the hypothesis about subscription platform launch being more beneficial for games in less occupied genres.

## Explanatory research

In the explanatory research part, I will aim to study the impact of several focal variables on the popularity and review trends in the pre-launch and post-launch periods on the gaming subscription platform. By grouping my observations based on different budgets of the game, franchising and exclusivity among others, I will try to define the most relevant features of the game which determine its post-launch performance. Then, in the predictive research part, I will build a model assessing the best timing of the launch given the features highlighted in the explanatory model.

My explanatory research will consist of 3 models: the Latent Dirichlet Allocation model for topic modeling of the reviews, the Sentiment Analysis of the reviews and the analysis of reviews density.

### LDA model

Latent Dirichlet Allocation (LDA) is a method widely used in online product review analysis (see e.g.  Tirullinai and Tellis 2014). It was originally developed for soft-clustering large amounts of textual data to uncover hidden structures. It assumes that documents (in my case reviews) are composed of topics, which consist of words from a vocabulary. The goal is to automatically discover the latent topics (e.g. crash reports or gameplay overview) in a document collection and understand how each document exhibits them. LDA belongs to the family of mixed membership models, where each word and topic have partial membership probabilities. The output of LDA includes groups of words (topics) with their membership probabilities and the proportions of these topics in each document. Researchers typically limit the output to a small number of high-probability words and assign topic labels based on their interpretation.

To properly set up the model researcher needs to first decide on the number of topics $k$ to use, which is usually done through cross-validation of different values of the $k$ parameter. The quality of the model is evaluated based on perplexity, which shows the performance of the model in representing the held-out test data and coherence measuring the semantic similarity of the top words in each topic.

To implement this model, I first cleaned the review data, removed the stop words and stemmed the review text. I also removed the words “play” and “game”, as their high frequency would deteriorate the model’s results and interpretability. Then I ran the cross-validation in order to find the appropriate number of topics. After checking the coherence and perplexity parameters

I was left with three possible models featuring similar performance: 8, 10 and 12 topic models. After assessing the interpretability of the results of different model iterations I decided to use the 12-topic model.

**LDA results**

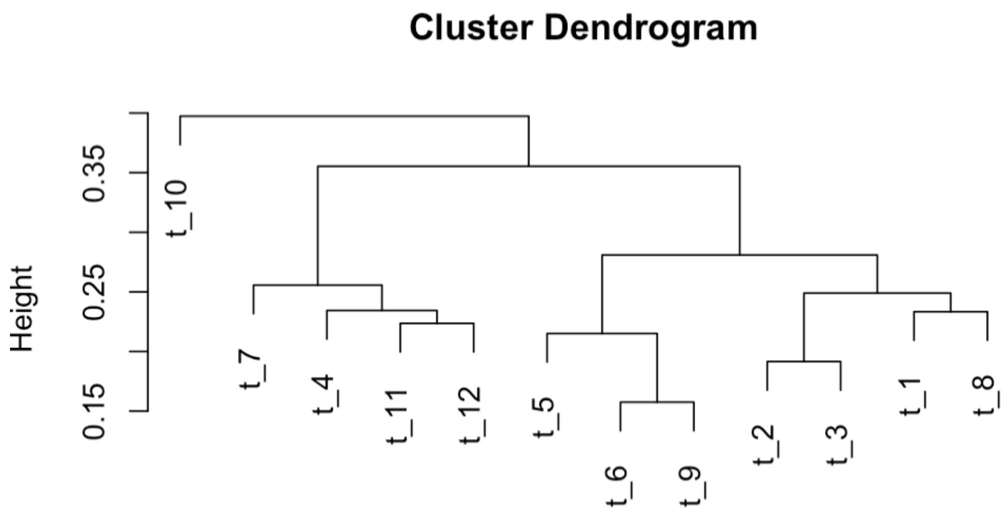


*Figure 3. Cluster Dendrogram was created based on the linguistic distance between LDA topics*

| Rank | t_1 | t_2 | t_3 | t_4 | t_5 | t_6 | t_7 | t_8 | t_9 | t_10 | t_11 | t_12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Money Worth* | *Gameplay* | *Gameplay* | *PC Setup* | *Build* | *Story* | *Multiplayer* | *Review* | *Story* | *Emoticon* | *Download* | *Crash* |
| 1 | pass | time | charact | pc | build | fun | friend | review | stori | thumbs | download | crash |
| 2 | bui | enemi | player | control | love | stori | fun | peopl | love | face | instal | time |
| 3 | xbox | boss | time | run | fun | feel | server | star | fun | fac | microsoft | fix |
| 4 | dlc | control | peopl | set | citi | love | multiplay | bad | amaz | smiling | launcher | bug |
| 5 | monei | feel | fight | xbox | add | charact | onlin | dont | time | heart | xbox | save |
| 6 | releas | fun | fun | issu | time | lot | player | im | charact | ey | updat | load |
| 7 | free | fight | dont | fp | explor | fallout | fix | love | puzzl | hand | fix | start |
| 8 | worth | bad | match | graphic | lot | world | love | rate | recommend | ef | launch | screen |
| 9 | time | level | team | fix | space | time | connect | kid | feel | red | time | hour |
| 10 | pai | combat | mode | screen | hour | combat | updat | hate | music | fire | pc | issu |
| 11 | version | kill | server | version | base | enjoi | xbox | fun | enjoi | joi | window | updat |
| 12 | pc | hard | bui | mous | planet | graphic | op | lol | art | crying | issu | progress |
| 13 | bought | bore | ubisoft | crash | map | pretti | issu | life | graphic | grinning | error | glitch |
| 14 | wast | hit | monei | consol | dlc | rpg | crash | gui | style | tears | store | fun |
| 15 | dont | weapon | broken | keyboard | car | system | join | read | experi | beaming | minecraft | minut |
| 16 | wait | ai | spam | perform | sim | hour | unit | stop | beauti | sign | app | freez |
| 17 | price | beat | trash | frame | updat | seri | lag | cry | combat | clapping | account | stuck |
| 18 | mod | mechan | win | port | ship | weapon | time | watch | rate | sunglass | start | complet |
| 19 | love | move | bad | option | surviv | worth | add | comn | hour | angry | halo | star |
| 20 | consol | run | fix | bad | start | fan | lot | listen | absolut | male | version | dai |

*Figure 4. Top 20 words with the highest term probability in each topic*

The table in Figure 4 shows the words with the highest probability to occur in each topic. It allows us to derive interpretations of each topic. The dendrogram in Figure 3 above shows the linguistic distance between the topics, grouping those topics into similar theme sets.

Based on those results we can distinguish 6 main themes covered in the reviews. First is the Technical theme which is related to the download process of the game, PC equipment used by the reviewers and the potential crashes and bugs occurring (topics $t_4$, $t_{11}$ and $t_{12}$). The second theme consists of reviews that describe the overall Gameplay experience, including the mechanics of the game, the fighting model as well as the single-player campaigns (topics $t_2$ and $t_3$). The next theme group is in general about the Story and the plot of the game, including an opinion about the characters, music and graphics (topics $t_6$ and $t_9$). The next themes are the topics that cover other game features, with $t_7$ representing the Multiplayer experience and $t_5$ relating to the build and exploration parts of the gameplay. Topic $t_1$ is particularly interesting, because it gathers reviews with mainly negative opinions about the monetary value of the title, often posing it as the software not worth paying a significant amount of money for. In the reviews scoring high in the topic $t_8$, we can see that they are mostly focused on replying to other reviewers in order to defend a particular game. The last one is the topic $t_{10}$ which gathers all of the emoticons used in the reviews.

**LDA regression**

In the next step, I run three regression models using Technical, Story and Cost-effectiveness themes as decision variables in order to find the possible relations between those variables and the five focal variables (Budget, Exclusivity, Franchise, Genre and In-game Purchases) introduced in the Data Section that I deem relevant for my research. The choice of themes was dictated by the potential managerial relevance of my research. Also note that the Genre is shown as an indicator splitting games into the common and uncommon genres, as explained in the Data section.

Above that, I also check the interaction between those focal variables and the IsAfterGP boolean indicating whether the review was posted after the game entered the Game Pass platform. That allows me to measure the impact of the subscription platform entry on the variable relations.

The formula for the regression models is shown below (note that the only difference between the models is the decision variable used). The last part denotes the interactions between the first five focal variables and the sixth variable indicating whether the review was posted after the game entered the Game Pass platform. The results of the regression with the coefficients and the p-values can be seen on Figure 5.

$$\begin{aligned} Story\ or\ Technical\ or\ Cost\text{–}effectiveness \\ = \alpha + \beta_1 UncommonGenre + \beta_2 Exclusivity + \beta_3 InGamePurchases \\ + \beta_4 Franchise + \beta_5 Budget + \beta_6 IsAfterGP + (1 - 5\, Variables) * IsAfterGP \\ + \varepsilon \end{aligned}$$

| | Story | | | Technical | | | Cost-effectiveness | | | Gameplay & Multiplayer | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Coefficient | P.Value | P_Score | Coefficient | P.Value | P_Score | Coefficient | P.Value | P_Score | Coefficient | P.Value | P_Score |
| (Intercept) | 0.48 | < 0.001 | *** | 0.29 | < 0.001 | *** | 0.16 | < 0.001 | *** | 0.05 | < 0.001 | *** |
| UncommonGenre_None | 0.04 | < 0.001 | *** | 0.03 | < 0.001 | *** | 0 | 0.403 | | -0.07 | < 0.001 | *** |
| Exclusivity_None | -0.07 | < 0.001 | *** | -0.13 | < 0.001 | *** | 0.02 | < 0.001 | *** | 0.18 | < 0.001 | *** |
| Exclusivity_PC | 0.07 | < 0.001 | *** | -0.03 | 0.006 | ** | 0.01 | 0.143 | | -0.06 | < 0.001 | *** |
| In.game.purchases_None | 0 | 0.573 | | -0.02 | < 0.001 | *** | -0.02 | < 0.001 | *** | 0.04 | < 0.001 | *** |
| Franchise_None | 0 | 0.76 | | 0.04 | < 0.001 | *** | -0.01 | < 0.001 | *** | -0.03 | < 0.001 | *** |
| Budget_Medium budget | -0.11 | < 0.001 | *** | -0.03 | < 0.001 | *** | 0.01 | 0.088 | . | 0.14 | < 0.001 | *** |
| Budget_Superstar | -0.22 | < 0.001 | *** | 0.05 | < 0.001 | *** | -0.01 | 0.073 | . | 0.17 | < 0.001 | *** |
| IsAfterGP_TRUE | -0.14 | < 0.001 | *** | -0.01 | 0.316 | | -0.03 | < 0.001 | *** | 0.18 | < 0.001 | *** |
| UncommonGenre_None:IsAfterGP_TRUE | 0.01 | 0.015 | * | 0.01 | 0.022 | * | -0.01 | 0.006 | ** | -0.01 | 0.005 | ** |
| Exclusivity_None:IsAfterGP_TRUE | 0.02 | < 0.001 | *** | 0.12 | < 0.001 | *** | -0.01 | 0.077 | . | -0.13 | < 0.001 | *** |
| Exclusivity_PC:IsAfterGP_TRUE | 0.05 | < 0.001 | *** | 0 | 0.877 | | -0.02 | 0.015 | * | -0.02 | 0.024 | * |
| InGamePurchases_None:IsAfterGP_TRUE | 0.09 | < 0.001 | *** | -0.03 | < 0.001 | *** | 0.02 | < 0.001 | *** | -0.07 | < 0.001 | *** |
| Franchise_None:IsAfterGP_TRUE | 0.04 | < 0.001 | *** | -0.1 | < 0.001 | *** | -0.01 | 0.034 | * | 0.07 | < 0.001 | *** |
| Budget_Medium budget:IsAfterGP_TRUE | 0.06 | < 0.001 | *** | 0.03 | < 0.001 | *** | 0.01 | 0.001 | ** | -0.1 | < 0.001 | *** |
| Budget_Superstar:IsAfterGP_TRUE | 0.1 | < 0.001 | *** | 0.04 | < 0.001 | *** | 0.01 | < 0.001 | *** | -0.15 | < 0.001 | *** |

*Figure 5: Coefficients of the regression with Story, Technical, Cost-effectiveness, and Gameplay & Multiplayer LDA themes as the decision variables*

The story theme which on average accounts for 48% of the review content decreases by 14 pp after the Game Pass launch. At the same time, the Gameplay & Multiplayer theme increases by 18 pp after the Game Pass launch, absorbing most of the negative dynamics of the Story theme. However, the overall net outcome is positive – the total of the Story and Gameplay & Multiplayer themes share increases after the Game Pass launch. That is beneficial for the developers as the game reviews after launch have a higher focus on the overall gameplay experience.

Another interesting insight is the positive interaction coefficient between the superstar and medium budget and the IsAfterGP = TRUE for the Technical theme. It means that Game Pass users tend to write more about the technical topic in the superstar and medium-budget game reviews, often complaining about the potential bugs and technical progress. This high proneness of the higher budget games towards the technical issue criticism hints that the developers should avoid releasing technically unstable games on the subscription services.

The topic modeling results also show that the score of the third theme in which reviewers talk about the cost-effectiveness of purchase (often in a negative way) decreases after the subscription platform entry, implying that the potential lack of cost-effectiveness of a particular title diminishes when users access it from a subscription library.

Looking at the scores of the Franchise variable we can observe that the non-franchised games experience a slight shift from technical and cost-effectiveness-related themes to topics focused on the general gameplay experience and a plot of a game. On the other side, franchised games see a substantial rise in technical-related topics which can be caused by an increased number of crash reports.

## Sentiment Analysis model

Sentiment analysis, also known as opinion mining, is a computational approach employed to automatically classify textual data into positive, negative, or neutral sentiment categories. It involves preprocessing the data, creating a sentiment lexicon, performing sentiment classification using rule-based methods or machine learning algorithms, and aggregating sentiment at different levels. The results are evaluated using metrics such as accuracy and interpreted to gain insights for decision-making and opinion analysis. Sentiment analysis finds applications in various domains, including product reviews and newspaper analyses.

In my model, I am using the Hu and Liu (2004) dictionary to find the sentiment score of each word in the pre-processed dataset with the reviews split into sentences (no stemming done as the form of the word is meaningful). Then I apply the polarity algorithm to calculate the overall sentiment score of each sentence in the review, accounting for the amplifier and deamplifier words and then calculating the sum of the per-sentence sentiment score for all reviews.

### Sentiment Analysis results

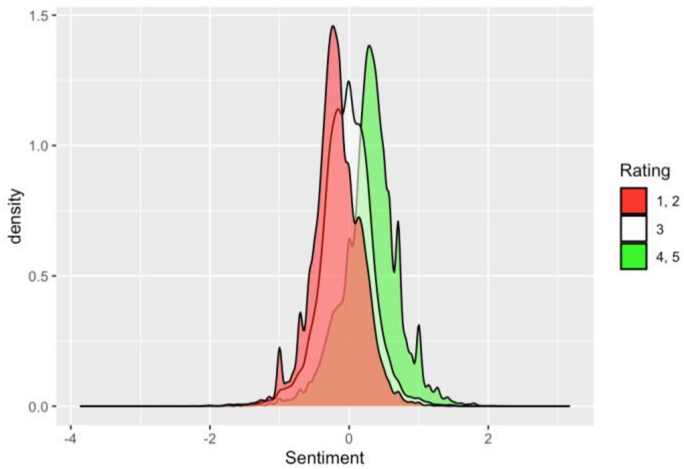


*Figure 6. Density plot showing sentiment scores of different rating groups (reviews with sentiment score = 0 are not shown to improve the presentation)*

| Sentiment Score | Count | Rating |
|---|---|---|
| **< -1** | 1471 | 2.33 |
| **-1-0** | 76392 | 2.26 |
| **0** | 43817 | 3.16 |
| **0-1** | 104750 | 4.01 |
| **> 1** | 3458 | 4.73 |

| Rating | Count | Sentiment Score |
|---|---|---|
| 1 | 67697 | -0.15 |
| 2 | 20765 | -0.12 |
| 3 | 19809 | -0.04 |
| 4 | 26300 | 0.14 |
| 5 | 95317 | 0.27 |

*Figure 7. Count and average rating of the reviews in different sentiment score categories (left) and average sentiment score of the reviews in each rating group (right)*

Figures 6 and 7 above show the results of the sentiment analysis. Sentiment is the sentiment score of each review while the rating is the number of stars given in each review to the game. The density plot shows that in most cases the sentiment score of the review complies with the rating given by the reviewer (note that I am filtering out the reviews with sentiment scores equal to 0 from the density plot for better visualization). Interestingly though, the distribution of reviews with 3 stars is slightly skewed to the right, suggesting that those reviews tend to be more negative.

The table in Figure 7 confirms that the sentiment score projects the rating of the review. Reviews with positive sentiment scores on average received 4 or more stars in the rating. Moreover, we can see that over 70% of all reviews are either 1 or 5 stars, which proves that this review set is imbalanced in these terms. In fact, this imbalance can be very often observed in the review analysis and is usually an outcome of a general behavioristic approach towards writing reviews – people tend to do it more often when they are either positively or negatively touched by the experience of using a certain product.

**Sentiment Analysis regression**

In the next step, I run two regression models both on the Sentiment Score and Review Rating in order to find the possible relations between those variables and the same set of focal variables and interactions that were used in the LDA regression.

The formula for both regression models is shown below (note that the only difference between the two models is the decision variable used). The last part denotes the interactions between the first five focal variables and the sixth variable indicating whether the review was posted after the game entered the Game Pass platform. The results of the regression with the coefficients and the p-values can be seen on Figure 8.

$$\begin{aligned} &Sentiment\ or\ Rating \\ &\quad = \alpha + \beta_1 UncommonGenre + \beta_2 Exclusivity + \beta_3 InGamePurchases \\ &\quad + \beta_4 Franchise + \beta_5 Budget + \beta_6 IsAfterGP + (1 - 5\ Variables) * IsAfterGP \\ &\quad + \varepsilon \end{aligned}$$

The first insight that we can derive from the analysis is that the reviews posted after the Game Pass launch on average feature lower ratings and lower sentiment scores which are denoted by the negative coefficients for the IsAfterGP = TRUE variable.

| | Sentiment Score | | | Review Rating | | |
|---|---|---|---|---|---|---|
| Variable | Coefficient | P.Value | P_Score | Coefficient | P.Value | P_Score |
| (Intercept) | 0.3 | < 0.001 | *** | 4.33 | < 0.001 | *** |
| UncommonGenre_None | -0.01 | 0.093 | . | -0.03 | 0.051 | . |
| Exclusivity_None | -0.13 | < 0.001 | *** | -0.63 | < 0.001 | *** |
| Exclusivity_PC | 0.06 | < 0.001 | *** | 0.36 | < 0.001 | *** |
| InGamePurchases _None | -0.01 | 0.193 | | -0.03 | 0.041 | * |
| Franchise_None | -0.01 | 0.12 | | 0.09 | < 0.001 | *** |
| Budget_Medium budget | -0.11 | < 0.001 | *** | -0.38 | < 0.001 | *** |
| Budget_Superstar | -0.16 | < 0.001 | *** | -0.9 | < 0.001 | *** |
| IsAfterGP_TRUE | -0.18 | < 0.001 | *** | -0.95 | < 0.001 | *** |
| UncommonGenre_None:IsAfterGP_TRUE | 0 | 0.905 | | 0.1 | < 0.001 | *** |
| Exclusivity_None:IsAfterGP_TRUE | 0.09 | < 0.001 | *** | 0.51 | < 0.001 | *** |
| Exclusivity_PC:IsAfterGP_TRUE | -0.01 | 0.397 | | 0.03 | 0.593 | |
| InGamePurchases_None:IsAfterGP_TRUE | 0.06 | < 0.001 | *** | 0.37 | < 0.001 | *** |
| Franchise_None:IsAfterGP_TRUE | 0.01 | 0.067 | . | 0 | 0.899 | |
| Budget_Medium budget:IsAfterGP_TRUE | 0.07 | < 0.001 | *** | 0.22 | < 0.001 | *** |
| Budget_Superstar:IsAfterGP_TRUE | 0.07 | < 0.001 | *** | 0.22 | < 0.001 | *** |

*Figure 8: Coefficients of the regression with Sentiment Score and Review Rating as the decision variables*

This effect is even more notable for the Indie category, as the coefficients for Medium Budget and Superstar interactions with the IsAfterGP = TRUE are positive indicating that they experience a higher decrease in the review rating and sentiment after the launch on Game Pass. It shows that Game Pass users are more rigorous in their reviews, which could potentially be an outcome of their better experience in testing different new titles (Microsoft (2022) claims that Game Pass subscribers play on average 40% more games). That also hints to the indie game developers that they should expect lower review ratings after the launch of Game Pass.

However, we can also see that in general Indie games receive reviews with the highest sentiment score and rating while Superstar games score the lowest in both. That can be caused by the overall highest expectations towards the Superstar games caused by their elevated prices. Moreover, with the launch of such a game on the subscription platform its price is no longer of significance, which explains the positive interaction coefficient between the Superstar games and the IsAfterGP = TRUE.

An interesting takeaway is also that the games without in-game purchases achieve majorly higher ratings and sentiment scores after the launch of the Game Pass which can be seen by analyzing the related interaction coefficient. That can be an outcome of the relatively negative approach of Game Pass players towards the additionally paid content.

Above that, the games that are not exclusive to either the PC platform or to the Microsoft devices on average receive the lowest sentiment and review rating before the launch on the Game Pass. However, they also suffer the lowest drop in in those scores after the release of the Game Pass.

## Review density

In order to measure the popularity of the game in different stages of its lifetime, I am using the reviews and their density as a proxy. This approach was already used by researchers in the past in gaming industry research. Zhu and Zhang (2010) state that online reviews can be a good proxy for an overall Word of Mouth of a game. Above that, Liu and Yong (2006) found that online movie reviews offer significant explanatory power for predicting both aggregate and weekly box office revenues.

For the review density analysis, I split the data into two subsets based on the initial launch strategy. The first subset consists of the games released on the Game Pass more than a month after their initial release whereas the latter set gathers games released on the Game Pass on day one. The explanation of each lifetime phase is shown in Figure 9. Note that both groups share the same last phase which is the phase after the launch of Game Pass.

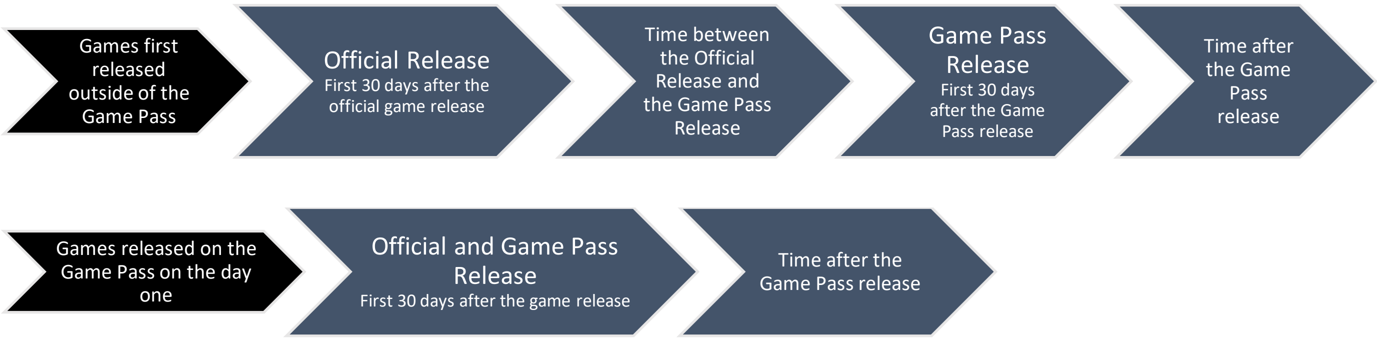


*Figure 9: Lifetime phases of a game released on the Game Pass*

To get the review density measure, I first calculated the time differences from the time when the review was created to (i) the official release of the game, and (ii) the launch time on the subscription platform. Then, I assigned each review to one of the lifetime phases as shown in Figure 9. In the last step, I counted the reviews in each phase for each title and divided it by the number of months that each title has been in a particular phase. The summary of this classification with the average review density for each phase can be seen in Figure 10.

| Phase | Review Density |
|---|---|
| Official Release | 126.2 |
| Official and GP Release | 305 |
| Between Official and GP Release | 10.5 |
| GP Release | 102.5 |
| After GP | 15.7 |

*Figure 10. Average review density for games in different phases*

As can be seen, the average game that did not launch on the Game Pass platform on the day one can retrieve around $\frac{\text{GP Release}}{\text{Official Release}} = \frac{102.5}{126.2} \sim 80\%$ of its official release popularity (measured in the review density) during its first month of the Game Pass release. Moreover, the games which were released on the Game Pass platform on day one on average received $\frac{\text{Official and GP Release}}{\text{Official Release}} = \frac{305}{126.2} \sim 2.4$ times more reviews during their launch month than the titles released solely on the classic platform.

Moreover, we can see that games present on the Game Pass platform after the initial month on average receive around 1.5x more reviews monthly than games that have not been launched yet on the subscription platform.

**Review density regression**

In the next step, I run five regression models on a review density of each of the five lifetime phases in order to find the possible relations between those variables and the same set of focal variables and interactions that were used in the previous regression models (excluding the IsAfterGP indicator as in this case I analyze the per game instead of a per review data so it is no longer relevant).

The formula for both regression models is shown below (note that the only difference between the models is the decision variable used). The results of the regression with the coefficients and the p-values can be seen on Figure 11.

$$\begin{aligned} &\textit{Review density for a particular lifetime phase} \\ &\qquad = \alpha + \beta_1 UncommonGenre + \beta_2 Exclusivity + \beta_3 InGamePurchases \\ &\qquad + \beta_4 Franchise + \beta_5 Budget + \varepsilon \end{aligned}$$

| | Official Release | | | Official & GP Release | | | Between Official and GP | | | GP Release | | | After GP Release | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | P.Value | | Coefficient | P.Value | | Coefficient | P.Value | | Coefficient | P.Value | | Coefficient | P.Value | |
| (Intercept) | 98.96 | 0.171 | | -32.37 | 0.86 | | 10.92 | 0.032 | * | 79.47 | 0.118 | | 5.86 | 0.274 | |
| UncommonGenre_None | 26.17 | 0.481 | | 10.42 | 0.908 | | -2.3 | 0.381 | | -8.88 | 0.725 | | 2.4 | 0.389 | |
| Exclusivity_None | -43.96 | 0.42 | | 142.67 | 0.31 | | -1.41 | 0.701 | | 35.99 | 0.327 | | 5.47 | 0.167 | |
| Exclusivity_PC | 113.78 | 0.268 | | 41.04 | 0.833 | | 12.33 | 0.047 | * | -22.13 | 0.711 | | 5.1 | 0.4 | |
| In.game.purchases_None | -49.44 | 0.192 | | -117.81 | 0.187 | | -2.85 | 0.273 | | -20.44 | 0.416 | | -6.57 | 0.016 | * |
| Franchise_None | 53.67 | 0.176 | | 314.52 | 0.003 | ** | -0.05 | 0.987 | | 47.11 | 0.089 | . | 8.88 | 0.004 | ** |
| Budget_Medium budget | 8.39 | 0.854 | | 253.29 | 0.028 | * | 3.29 | 0.322 | | 3.93 | 0.903 | | 5.47 | 0.119 | |
| Budget_Superstar | 142.99 | 0.004 | ** | 140.59 | 0.27 | | 5.53 | 0.104 | | -23.5 | 0.48 | | 5.21 | 0.167 | |

*Figure 11: Coefficients of the regression with average review density for different lifetime phases as the decision variables*

| Budget | Day One | < 1 month | > 1 & < 6 months | > 6 &< 12 months | > 12 & < 24 months | > 24 months |
|---|---|---|---|---|---|---|
| Indie | 61% | 4% | 3% | 10% | 8% | 14% |
| Medium budget | 57% | 2% | 9% | 4% | 7% | 20% |
| Superstar | 49% | 2% | 2% | 10% | 10% | 27% |
| **Franchise** | | | | | | |
| Yes | 49% | 2% | 3% | 10% | 10% | 26% |
| No | 62% | 3% | 6% | 8% | 7% | 14% |
| **Genre** | | | | | | |
| Uncommon | 57% | 1% | 7% | 13% | 7% | 16% |
| Common | 54% | 4% | 3% | 5% | 10% | 24% |
| **In-game purchases** | | | | | | |
| Yes | 54% | 4% | 6% | 10% | 11% | 15% |
| No | 56% | 2% | 4% | 8% | 7% | 24% |
| **Exclusivity** | | | | | | |
| Microsoft | 52% | 0% | 0% | 9% | 7% | 33% |
| PC | 73% | 4% | 0% | 0% | 8% | 15% |
| Non-exclusives | 54% | 3% | 6% | 9% | 9% | 19% |

*Figure 12: Distribution of games (% of all games) based on their timing of entry on Game Pass*

| Budget | Official | Official & GP | Before GP | GP Release | After GP | GP Launch |
|---|---|---|---|---|---|---|
| | *in reviews per month* | | | | | *in days* |
| Indie | 39.7 | 359.3 | 5.4 | 123.9 | 17.4 | 342.6 |
| Medium budget | 84.8 | 173.2 | 8.8 | 98 | 10.6 | 631.2 |
| Superstar | 231.5 | 354.3 | 15.4 | 88.9 | 17.6 | 644.7 |
| **Franchise** | | | | | | |
| Yes | 138.3 | 176.9 | 12 | 69.5 | 12.6 | 680.8 |
| No | 112.6 | 406.6 | 8.4 | 148.8 | 18.9 | 373.6 |
| **Genre** | | | | | | |
| Uncommon | 109.2 | 256.9 | 12 | 111.7 | 14.1 | 415.3 |
| Common | 144.7 | 348.1 | 9.1 | 94.5 | 17.1 | 629.1 |
| **In-game purchases** | | | | | | |
| Yes | 163.8 | 420.3 | 14.1 | 127.5 | 21 | 309.2 |
| No | 88.6 | 230.6 | 8.1 | 84.7 | 11.9 | 678.9 |
| **Exclusivity** | | | | | | |
| Microsoft | 268.4 | 428 | 13 | 43.9 | 13.9 | 627 |
| PC | 71 | 87.6 | 6.5 | 53.8 | 4.6 | 255 |
| Non-exclusives | 104.2 | 316.1 | 10.2 | 115.1 | 17 | 538.3 |

*Figure 13: Average review density in each Phase for different focal variables*

Moreover, I calculate the distribution of games based on their timing of entry on Game Pass grouping the observations based on the focal variables which can be seen on Figure 12 and the average review density for each phase on Figure 13. That in connection with the regression on the review density allows me to analyze the performance and utilization of different entry strategies for my set of the focal variables.

The Indie games on average enter Game Pass earlier than the other games with 61% of indie games entering the subscription platform on day one. It proves to be beneficial for them, as their popularity in the day one launch vastly outperforms the classic release strategy, with review density in the first month after the launch being 9x higher in the dual-launch strategy compared to the single-launch strategy Official Release. Moreover, I measure that the Indie games which do not launch on day one on Game Pass tend to receive 3x more reviews on their Game Pass launch than on the classic one and get on average 3.5x more reviews in the long term when being available on Game Pass compared to the period between official and Game Pass releases. These findings comply with the prior assumptions about indie developers being the biggest beneficiaries of the inform and persuade functions of the subscription platform launch derived based on the advertising theory literature.

In terms of popularity performance in different phases Superstar games significantly stand out among other categories. Most notably, they feature the highest post-official release popularity achieving an average of 230 reviews in the first 30 days after the official launch. This effect is also apparent in the regression with statistical significance. However, they also benefit from the release on the subscription platforms, with day one launch gathering on average 1.5x more reviews than the classic launch and the late subscription platform release generating on average 88.9 reviews in the first 30 days while also improving the long-term review density by over 10%. It proves that the late release on the subscription platform can be a good strategy for developers wanting to revitalize their game community. In fact, almost 40% of superstar games in my dataset have been launched on the Game Pass more than 1 year after the official release.

In the medium budget category, the positive effects of the subscription platform are less notable, although they are still relevant. The review density for the day one launch on Game Pass is lower than in the other categories, but it is still over 2x higher than in the singular release. Interestingly, the regression results show that the medium-budget games on average achieve the highest review density in this phase ceteris paribus. Moreover, medium-budget games gain on average 15% more reviews in the first month after the Game Pass release than in their official release suggesting that the revitalizing effect of the subscription platform launch is also apparent for this budget category.

The next focal variable in the analysis is the Franchise. The assumptions made in the conceptual framework suggest that the franchised games should be less probable to launch early on the subscription platform. That is because the relative importance of the inform and persuade advertising effects is lower for the games launching as a part of a series with an already established marketing image.

The results largely comply with the pre-assumptions – franchised games launched on Game Pass on average 1.8x later than non-franchised titles with only 49% of the franchised games being launched on day one on Game Pass versus 62% for franchised games and receiving much worse reception during their launch on Game Pass in terms of the popularity. The regression results further confirm those assumptions as the non-franchised games on average have higher review density in almost all phases ceteris paribus.

Proceeding forward, another variable put under analysis is the genre shown as the commonality of the particular genre. Note that each game can feature multiple genres and a particular genre is regarded as uncommon when its share in all of the games is at less than 15% as described in the Data section.

The initial hypothesis about the impact of the genre on the subscription launch and its outcomes derived based on past academic research in this topic hinted that games in the less occupied genres should enjoy higher interest than equivalents from more popular genres. This theory is motivated by the specificity of gaming platform users, who are in general more eager to test new games and try novel genres than the classic players.

The data partly support this hypothesis by showing, that almost 80% of games in uncommon genres are launched on Game Pass during the first year after the official release compared to 65% for common genres.

Above that, their review density during the first month after the Game Pass Launch slightly outperforms the average figure after the official release which is not the case for the games in the common genres. That proves that games in less occupied genres can indeed benefit from entering the subscription platform and often exceed their first-release popularity figures.

However, the average review density during the joint launch is substantially higher in the common genre, which can be attributed to the more established position of the titles in the common genres. Above that, the long-term review density after the Game Pass launch is higher for the mainstream games questioning the sustainability of the positive effect of uncommon genres. Those effects can be also observed in the regression model, although they are not significant which highlights the need for further research in this field in order to confirm the relevance of this effect.

The next analyzed focal variable is the In-game purchases. This variable indicates whether a game allows its players to purchase additional in-game content after the purchase of a core product. This is especially relevant for the case of the subscription platforms, as availability of the in-game purchases can substantially increase the profits generated after launch. In fact, figures published by Microsoft confirm that Game Pass users on average spend 45% more on in-game content. That shows that availability of in-game purchases is essential for choosing the correct entry strategy.

At first glance, this effect seems to be reflected in the data, with games that have access to in-game purchases having on average over a 2x smaller window between the official release and the Game Pass launch. However, when analyzing the distribution of the games in each entry period we can see that they are highly similar between the subsets with the major difference being titles that have launched on Game Pass later than 2 years after the official release. Those extreme cases drive the high average launch window in days for the subset without in-game purchases available. That is potentially a result of the relatively low popularity of the in-game additional content in older titles.

Moreover, the regression results show that the games without the in-game purchases perform worse in terms of the review density across all of the lifetime phases ceteris paribus. While it may seem counterintuitive at first, this relationship might actually exist but in the reverse direction. That is because developers of the more popular games may want to leverage their extensive audience by introducing additional in-game content therefore creating a correlation between this variable and the overall review density.

The last focal variable checks whether the game is exclusive to only PC devices, to all Microsoft devices (incl. Xbox and PC) or is universally available. That factor was invoked in the academic research as single- or multi-homing. Researchers proposed that while releasing software on a single platform can be favorable to its owner it is rather ineffective for the developer (unless he receives additional benefits directly from the platform owner). That is because the general outreach of the game which is released on a single platform is lower and the overall network effects generated by each platform that the game is available on are thus weaker.

That being said, we can see that the late launch of both Microsoft and PC exclusives on Game Pass brings a relatively low audience, with both subsets achieving much lower review density after the Game Pass launch compared to the official launch performance. Above that, both exclusive subsets enjoy higher review density during the joint launch compared to the single release hinting at the day-one launch being the best strategy for the exclusives. That also goes in line with the strategy employed by Xbox to release all of the Microsoft games on day one.

## Predictive Research

In the next part, I will use the findings from the explanatory part to create a predictive model aiming to predict the best launch timing on a subscription platform in months given the game characteristics and expected post-launch popularity.

As 55% of the observations have been released on day one, I need to use the relevant modeling technic to deal with the imbalanced dataset. Therefore, for the predictive analysis, I will be using the Gradient Boosting model which is an ensemble method based on the implementation of multiple Decision Trees. I will compare the performance and the results of this model with the benchmark Generalized Linear Regression model.

### Gradient Boosting theory

Gradient Boosting is a powerful machine learning technique that combines weak learners to create a strong predictive model. In my case, those weak learners are the Decision Trees. It iteratively improves the model's performance by focusing on errors made by previous models and adjusting instance weights, running each model on a different sample of a dataset.

Boosting algorithm runs sequentially, adjusting weights for each observation which then determines a sample probability of each of them. Higher weights are given to the misclassified observations, raising their probability of being selected for a training sample in the subsequent iterations.

The final model is an ensemble of Decision Trees, providing accurate predictions and capturing complex relationships in the data. It is widely used in various domains for classification, regression, and ranking tasks, performing exceptionally well when dealing with imbalanced data.

### Model Setup

In my model, I will aim to predict the Launch Timing of each game which is the number of months between the official game release and the launch on the Game Pass platform. For the independent variables I will be using the same set of focal variables as used in the explanatory research as listed in Figure 1 extended by the two additional variables. The first of them indicates whether the game is available on the new generation of consoles (Xbox Series X and Play Station 5). Those games can potentially reach a higher audience thanks to their availability on the new consoles.

The next variable measures the post-subscription platform launch performance. As my goal of the predictive analysis is to find the most optimal strategy of the subscription platform entry for a game developer which would maximize the post-launch popularity, I need to introduce a moderating variable which would account for this popularity increase.

Therefore, I decided to add the launch performance variable measuring the post-launch review density of the already games in my dataset. Thanks to this, the managers will be able to leverage the predictive model results by using the ICE plot calculated for the particular feature combination of their game receiving the optimal launch timing for each launch performance score. Then with the use of their perceived expectations of the launch performance of their title while also accounting for other factors not included in the model as the financial side of the subscription platform launch managers will be able to select the optimal time window.

The decision of such a model setup is also dictated by the fact that solely based on the review density as a popularity measure, we are not able to assess the actual success of the game launch on the subscription platform as that success is relative to the developer's expectations. That is why I leave the decision of choosing the expected launch performance to the managers.

The launch performance measure is calculated as the number of reviews during the first month after the Game Pass release for late Game Pass launches or as half of the number of reviews in the first month after the day one Game Pass release to account for the popularity not generated by the Game Pass launch (the half is used for the dual launch as the mean, median and the standard value of the review density values for the singular Official Release and the singular Game Pass Release is very similar which suggests that 50:50 is the most optimal distribution for the dual-launches).

To properly set up a Gradient Boosting model I need to perform a tuning procedure to find the optimal values of the model parameters maximizing the $R^2$ performance measure. Those parameters are the number of weak learners (Decision Trees) used in the ensemble and the maximum depth of each tree. In my model the best result of $R^2 = 0.345$ was produced by the model with 21 trees with a maximum depth of 4 nodes.

As a benchmark, I am using the Generalized Linear Model with the Poisson distribution, as it suits better to the imbalanced data than the normal distribution regression. This model produced the $R^2 = 0.332$ which is slightly worse than the Gradient Boosting model.

## Results

As the Gradient Boosting is the Black Box model, I am not able to visualize the coefficients or the model formula. That is why I will be using a set of global and local interpretation methods to visualize the results of this model. The results will be presented as follows: first, the variable importance of the Gradient Boosting model will be shown followed by the coefficients table of the benchmark Poisson regression to gain a brief knowledge about the model structure and the results. Second, the model performance will be measured. Third, the Individual Conditional Expectation plots will be presented to provide managers with insights into the optimal launch timing for their game.

### Global Interpretation – Variable Importance and model coefficients

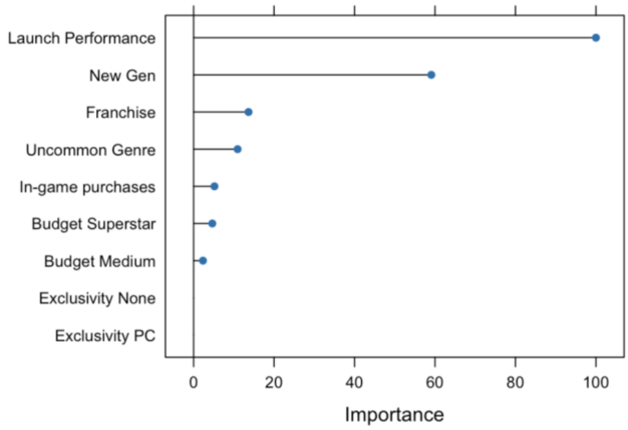


*Figure 14: Variable Importance in the Gradient Boosting Model*

In Figure 14 the importance plot of the Gradient Boosting model is presented. The variable with the highest importance is the Launch Performance. However, this result is unsurprising as the explanatory section of the report already shows that the day one launch is on average generating significantly larger review density during the first month, which already suggested that the significant correlation between the launch timing and its performance is to be expected. The other important variables are the Generation of consoles followed by the Franchise, Genre, In-game purchases and Budget category.

| Variable | Coefficient | p Value | Significance |
|---|---|---|---|
| (Intercept) | 2.26 | < 0.001 | *** |
| FranchiseNone | -0.18 | < 0.001 | *** |
| In.game.purchasesNone | 0.16 | < 0.001 | *** |
| Next.GenNone | -0.65 | < 0.001 | *** |
| `BudgetMedium budget` | 0.09 | < 0.001 | *** |
| BudgetSuperstar | 0.09 | < 0.001 | *** |
| ExclusivityNone | 0 | 0.994 | |
| ExclusivityPC | 0.11 | < 0.001 | *** |
| UncommonGenreNone | 0.27 | < 0.001 | *** |
| LaunchPerf | -1.67 | < 0.001 | *** |

*Figure 15: Coefficients of the Poisson Regression model, followed by p value and Significance (Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1)*

Figure 15 shows the coefficients of the benchmark model. They deem similar results in terms of the importance as in the gradient boosting model. However, coefficients allow us to see the direction of each effect. The variables negatively related to the launch timing are launch performance, the old generation of consoles and not-franchised games. Hence, the launch timing decreases with the increase in the expected launch performance. Moreover, games not available on the new generation of consoles and games that are not part of a franchise should on average be launched earlier.

**Model Performance**

| Performance measure | Gradient Boosting | Poisson Regression |
|---|---|---|
| RMSE (in months) | 30.5 | 28.8 |
| % of right guesses (with ±6 months error margin) | 50% | 46% |

*Figure 16: Performance measures for Gradient Boosting and Poisson Regression models*

As the model is using mostly categorical variables (with the exception of the Launch Performance measure) it is expected that its performance might be limited. It is confirmed by the Root Mean Squared Error measure which achieves 30.5 months for the Gradient Boosting model and 28.8 months for the Poisson Regression. That translates to roughly 2.5 years of the average difference between the actual and predicted variables. However, when we look at the % of right guesses measure which counts a prediction as a positive when it is less than 6 months before or after the actual launch timing values, we can see that the Gradient Boosting model achieves a 50% success rate. Taking into account the limitations of the predictive model I consider this performance as satisfactory.

**Local Interpretation – Individual Conditional Expectation plots**

In order to study the impact of each variable on the final prediction I will be using ICE plots, which display instance prediction with the feature changes for each instance in the dataset. The feature which I will be confronting against the dependent variable is the launch performance and the other variables will be used as the grouping variables. First, I am calculating the predicted launch timing based on the given launch performance inputting values between 0 and 250 for the latter variable and then I will calculate the average predictions per each feature subgroup based on the other model variables.

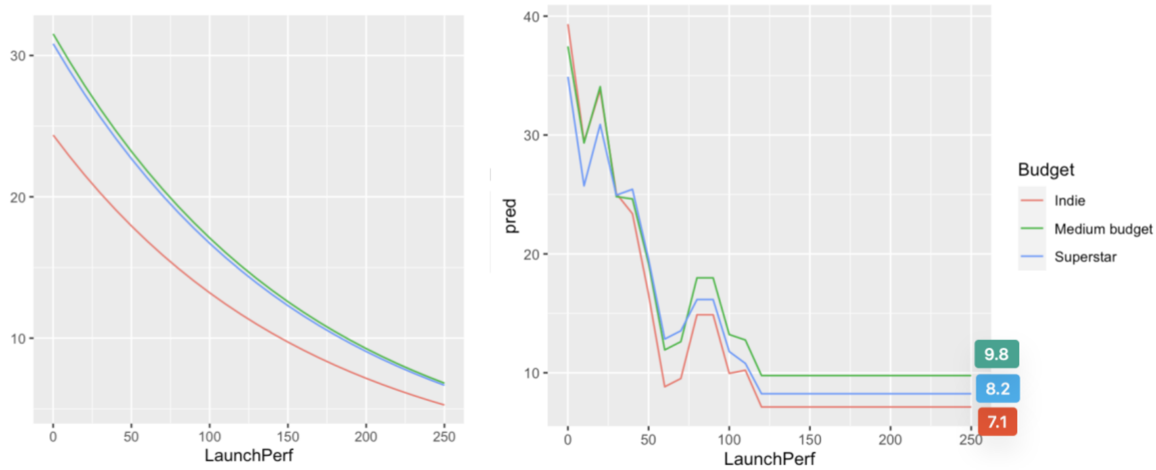


*Figure 17: Individual Conditional Expectation plots for the Gradient boosting model (on the right) and Poisson Regression model (on the left) for each Budget category*

As can be seen in Figure 17, the Indie games are in both models predicted to launch earliest giving the same expected launch performance. It can be also noted, that in the Gradient Boosting model, the predicted launch timing settles at around 7 months for Indie games, 8 for Superstar games and 10 for medium-budget titles. This suggests that those timeframes are the potential optimal launch windows for each group given the aim of launch performance maximization.

In the regression model, the medium budget and superstar games give very similar predictions, with the Indie category being the clear distinction from others with the lowest predicted launch timing for each given launch performance.


*Figure 18: Individual Conditional Expectation plots for Gradient boosting model for each Franchise (on the left) and a new generation of consoles (on the right) category*

Furthermore, the predicted launch timing is on average substantially higher for franchised games compared to non-franchises, which complies with the theory assumptions that the franchises are less likely to benefit from the inform and persuade effects of the early subscription platform launches due to their usually already established game audience.

The new generation of consoles also positively impacts the predicted launch timing significantly increasing the number of months after launch needed to achieve the given launch performance. What is especially interesting in this category are the very high launch predictions for low launch performance values. That is caused by the number of relatively old games which were made backward compatible on the new generation of consoles and launched on the Game Pass platform achieving rather poor reception.

**Prediction Example**

Both models can be also used for single observation predictions. To visualize that, I chose to predict the optimal launch strategy given the expected launch performance for the game Age of Empires II: Definitive Edition, which is a superstar not available on the new generation of consoles, PC exclusive, part of a franchise, uncommon genre title with available in-game purchases.

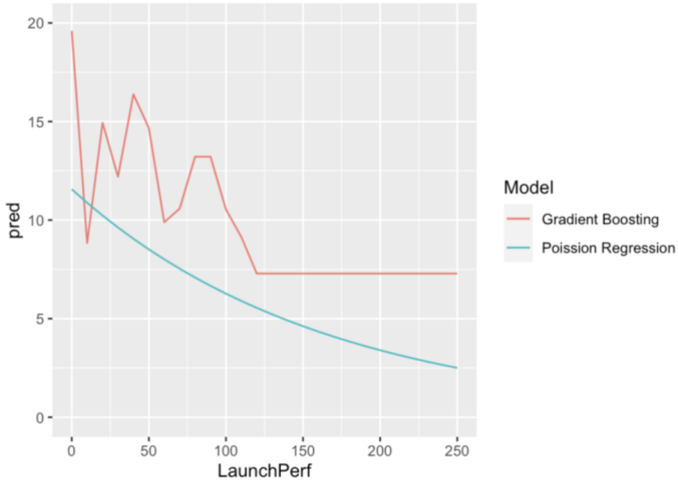


*Figure 19: Prediction for the Age of Empires II: Definitive Edition game ran using both models for a given range of launch performance*

Both models produce different results for the low launch performance figures, however for the launch performance above 100 they predict a similar launch timing ranging between 2.5 and 7.5 months. In order to find the exact launch window, the game developer should input the launch performance expected from the Game Pass launch and see the model's projection.

# Discussion and Implications

By observing how launching a game on a subscription platform boosts its popularity I find that this effect is not only dependent on the game category and its features, but also on its entry strategy. I also establish the predictive model which aims to find the most beneficial entry strategy given the game characteristics.

## Implications for Theory and Research

Research in domains of subscription platforms as well as the gaming industry research can use my findings. First, with regard to the indirect network effects and the positive effect of the installed base prior research rarely distinguished indie developers and their potential benefits. I show that those developers are the biggest beneficiaries of the subscription platform launch, often achieving similar post-subscription platform launch performance as more established titles and massively exceeding its popularity figures during their official non-subscription launch. I prove with this analysis that the advertising theory and the need to inform and persuade applies most predominantly to those smaller software studios luring them to launch their product on the subscription platform in the early stages of their lifetime. Above that, I show that this effect is diminished in cases when the software is a part of a franchise, as it usually has an already more established position in the market as a part of a series.

I also reveal that superstar titles are often launched on subscription platforms on day one, showing that the implications from the streaming industry theory about the investments in high-budget titles in order to gather new subscribers also apply to the gaming industry. Although I was not able to measure the indirect network effects of the superstar software launches on the platform as I did not have access to the detailed user data, the market data shows that the userbase of the Game Pass subscription platform has almost tripled since the start of the day-one launch strategy for superstars in 2020.

Pertaining to the game variety theory I show that the games in the uncommon genres enjoy relatively better reception during their subscription platform launches compared to their official release popularity figures. That extends the theory introduced by Zhu et al. (2012) stating, that customers seek variety on the gaming platforms with high platform-wide game variety increasing the overall indirect network effects.

## Implications for Managers

My study shows managers how to select the best timing of the launch on the subscription platform based on the game specifications. Among the existing approaches, there hasn't been similar academic research aiming to also answer this question. To find the best launch timing, managers can look at the figure presented in the predictive research part and find the relevant category based on their expected launch performance. The most relevant insight is that the games in the Indie categories as well as non-franchised games and titles not available on new consoles should be on average launched earlier than the rest.

I also reveal with the use of topic modeling and sentiment analysis that while the overall average sentiment decreases after the subscription platform launch, the topics covered in the reviews tend to shift from the cost-effectiveness topic into the story and gameplay-related topics. This is important for the game developers as creates more field for the discussion about the overall gameplay experience of the title, thus enlarging its overall word of mouth.

Moreover, my topic modeling study shows that superstar games often witness a significant increase in technical and crash-related topics. That poses a challenge to the superstar game developers to assure sufficient game playability from the technical side before the launch of the subscription platform as its users are especially prone to technical problems.

On the other hand, my research shows that games after the launch on the subscription platform receive fewer reviews aimed at the relativeness worthiness of buying a game referring to its cost-effectiveness. That finding makes early subscription platform launch a good strategy for the games which receive negative word of mouth regarding their price-to-quality ratio, as from game pass users' perspective the marginal price of downloading each game is negligible.

| Game Feature | Impact on the earliness of the launch |
|---|---|
| Indie | Positive |
| Medium Budget | Negative |
| Superstar | Negative |
| Franchise | Negative |
| Uncommon Genre | Low Positive |
| Microsoft Exclusive | Positive |
| In-game purchases | Low Positive |
| New Gen. consoles | Positive |

*Figure 10:: Average effect of different game features on the predicted earliness of the optimal launch timing based on the prediction model results*

The summary of the overall average effects on the predicted launch strategy based on the prediction model is presented in Figure 20. It shows the predicted effect of several game features on the earliness of the optimal launch on the subscription platform. Based on that, managers can assess the relative launch timing strategy for their software

## Limitations and Further Research

Limitations of my study suggest further research. First, I focused only on one subscription platform which might introduce a bias in the dataset. In the future possibly more subscription platforms would become available hence extending the data availability.

Second, as the gaming subscription industry is relatively fresh and multiple games in my dataset have been released before the establishment of the Xbox Game Pass platform, the trends measured in the analysis may be still vague and dynamic. Potentially in subsequent research in the future, better distinguishment of different market-specific effects will be made available due to the increased maturity of the market.

Third, my research was limited by the available data points for each game. The potentially relevant variables as the usage of each game or the financial data are not disclosed to the public, therefore I was not able to attain access to it. This type of data would extend the explanatory and predictive power of my research by assessing both the review word of mouth, the overall game player base in time and most importantly, the financial performance after the subscription platform release.

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