The Effect of Price Changes on the Box Office for the Cinema Industry: Results from Randomized Field Experiment

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Abstract

The cinema industry is a highly competitive and dynamic market. Due to the features of the market, price changes have shown a growing interest in this sector. These strategies profoundly influence consumer behavior, consumption, and, consequently, box office revenue. Previous research has found a negative influence on the relationship of price with revenue. This thesis will deliver the primary outcomes of a field randomized experiment conceived to examine the effect of price changes on revenue inside the cinema industry. The experiment consisted of varying ticket prices for different rooms, with some rooms serving as control groups.

For the data to be categorized as reliable, accurate, reliable and ensure robust outcomes, there was the need to prepare the data.

Four regression models were built on understanding demand and revenue elasticity in the cinema theatre, examining the relationship between the number of tickets sold and price and revenue and price. Two simple regression models were created one for each result and two for multiple regression (expansion of simple regressions with adding covariates).

These findings contribute to expanding the knowledge inside the industry. The results from this study will be a worthy resource not only inside the cinema industry but also for future analyses on consumption, dynamic prices, and the decision-making process of other industries.

Keywords: Cinema; Randomized Experiment; Clusters; Price Changes; Box Office; Panel Data; Regression Analysis;

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Abstract

A indústria cinematográfica é um mercado altamente competitivo e dinâmico. Devido às características do mercado, as alterações de preço têm apresentado um crescente interesse neste setor. Esta estratégia influencia profundamente o comportamento e o consumo do consumidor e, consequentemente, a receita da bilheteira. Pesquisas anteriores encontraram uma influência negativa na relação do preço com a receita. Esta tese fornecerá os resultados primários de uma experiência de campo randomizada concebida para examinar o efeito das mudanças de preços na bilheteira da indústria cinematográfica. A experiência consistiu em variar os preços dos bilhetes para diferentes salas, com algumas destas salas a servir como grupo de controlo.

Para que os dados fossem categorizados como confiáveis, precisos e garantissem resultados mais confiáveis e robustos, houve a necessidade de preparar os dados.

Quatro modelos de regressão foram construídos a partir da compreensão da elasticidade, da procura e da receita no cinema, examinando a relação entre o número de bilhetes vendidos e o preço, e a receita e o preço. Foram criados dois modelos de regressão simples um para cada resultado e dois de regressão múltipla (expansão das regressões simples com adição das covariantes).

Estas descobertas contribuem para expandir o conhecimento dentro da indústria. Os resultados deste estudo serão um recurso valioso não só dentro da indústria cinematográfica, mas também para futuras análises sobre o consumo, preços dinâmicos e o processo de tomada de decisão de outras indústrias.

Palavras-chave: Cinema; Experiência Randomizada; Aglomerados; Alterações de Preços; Receita de bilheteira; Dados em Painel; Análise Regressão;

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1 Introduction

Across the last two decades, the importance and attention towards the motion picture industry have climbed precipitously. This industry is often linked with popcorn, celebrities, glamour, and excitement. However, the word that generally pops up when we think about the film industry is money and its economic weight in the global economy. In Portugal, from 2000 until the pandemic, this industry generated box office revenue ranging from 60.251 thousand euros to 83.190,6 thousand euros. During this period, spectators per thousand habitants varied from 1313,4 to 1878,9.

Nevertheless, due to the nature of the industry, this is a hazardous environment, and only some movies are blockbusters. This is why managers must be cautious when making decisions to prevent losses. This thesis aims to support managers by enhancing their strategic assessments and developing the prospects of profits. By answering the two following questions: Do price manipulations directly impact the revenues of this industry? Is it still meaningful for a manager to change the price?

Figure 1: Evolution of the cinema revenue in Portugal from 1990 to 2011

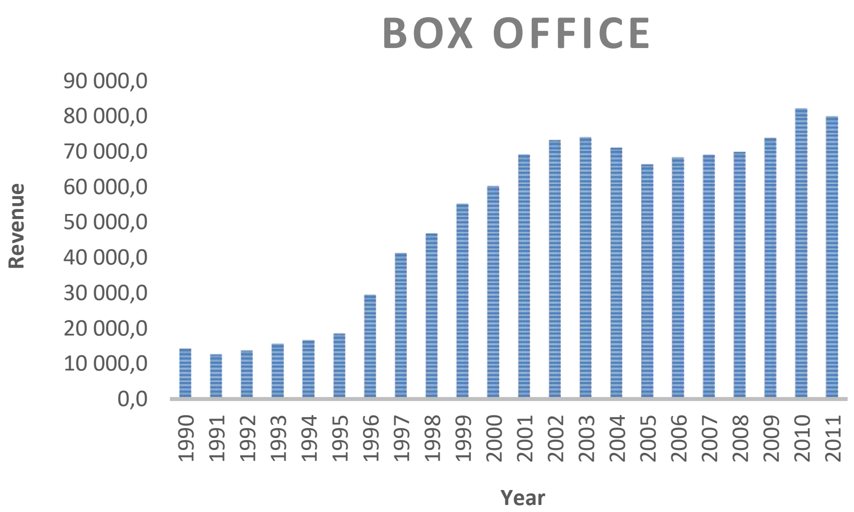
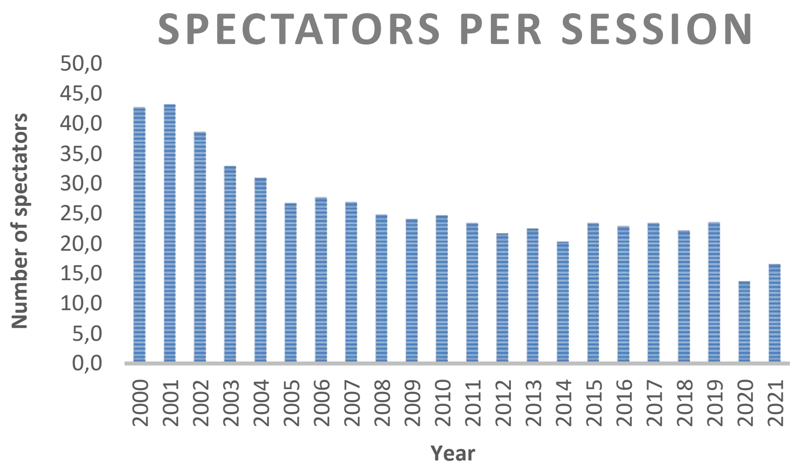


Figure 2: Evolution of the cinema attendance in Portugal from 2000 to 2021



Since there are not enough studies on this subject, several vital concerns for practice still need to be addressed. This study will be crucial. Furthermore, this paper informs students, firms, investors, and researchers regarding the impact of price variations on revenue and consumer choices. Assessing the outcomes from a randomized field experiment lets us manage unobserved factors that might impact ticket consumption. Lastly, we exhibit by what means the results of this experiment can be effectively linked from an organizational point of view to plan an approach that companies can generate price adjustments for this product to optimize revenue.

As mentioned, our investigation aims to contribute to the literature by adequately determining the claim regarding the significance of price manipulation in consumers. We carry on as follows. We assess the predictions of an empirical model employing the results from a randomized field experiment developed by a telecommunications company called ZOMA. This company led research employing their cinema business/rooms. A new set of ticket policies regarding price changes was added to the company's pricing strategy for almost two consecutive months. There were created clusters regarding the cinema's rooms to implement the new approach. The rest of the rooms remained at the usual prices. Specially we seek to answer is: How do price changes impact box office revenue and attendance in the cinema industry, and what perceptions can be achieved concerning optimal pricing strategies and profit boosting?

Hypothesis 1: There is not going to be a significant difference (less than 5%) between ticket policies in terms of revenue in the cinema industry.

Hypothesis 2: An increase in ticket price will lead to differences in the total amount of tickets acquired.

The main findings from the models are aligned with the literature review. Furthermore, movie age is one of the elements that impact box office revenues. New releases generate more revenue than older movies. The older the movie is, a tiny increase in the quantity of sold tickets is observed. New releases can be linked with thrill, enthusiasm, and novelty.

In the last years, several studies have been done regarding how mobile/online payment has become part of society's day and the advantages that come with it. Consumers who purchase tickets through the web ticket buy approximately more than customers through the app.

This thesis will exhibit an inverse relationship between price and quantity sold; thus, quantity sold tends to decrease when the price increases.

Our paper is organized as follows. First, it starts with reviewing the relevant literature on the influence of price variations on revenue and consumer choices. The second stage introduces the empirical context and experimental design, where a brief description of the company and the research provisions are clarified. The subsequent section proposes the methodology and data, where the strategy model will be presented, along with a description of the data used in the analyses and descriptive statistics. The fourth stage contains the study of the effect of price changes on revenue and the empirical results. Finally, section five summarizes the paper's main findings and presents conclusions.

2 Literature review

2.1 Movie industry

The cinema industry is a dynamic and complex business comprising film production, distribution, and exhibition. This industry began in the late 19th century with the creation of the first films with the help of the motion picture camera. Since then, the business has undergone massive modifications and encountered several challenges, including COVID-19. During this time, they were forced to close theatres, run at restricted capacity, delay the release of new movies, and face hesitancy from consumers to attend crowded inside areas (Mikos, 2020). Consequently, the industry suffered a huge impact, a decline in box office revenue, and a decrease in movies released.

Regarding the production and distribution of films, the industry is predominantly dominated by major film studios, like Disney, Universal Pictures, Warner Bros., and Paramount Pictures

(Gomery, 2003). Despite the dominance of these studios, the industry also incorporates minor parties like independent filmmakers and smaller groups. Moreover, both groups present different characteristics. The first group is associated with the most popular movies and has access to substantial talent, financial resources, and infrastructure. On the other hand, filmmakers generate significantly acclaimed movies, niche content, and documentaries while operating on a lower budget.

Despite the adversities faced through the years, the cinema's traditional business model will continue to encounter disputes and competition arising from streaming services, digital platforms, and television. Streaming platforms, like Netflix and Amazon Prime, are acquiring a substantial market share (Gaustad, 2019). Nevertheless, as the industry persists in adjusting and modernizing to developments and changing technologies, there will always be a space in the consumer's desire for the distinctive practice of watching movies in a cinema. Therefore, the industry will remain a considerable sponsor of the global economy and an essential entertainment home.

2.2 Box office

The movie industry creates revenue across various resources, comprising streaming services, merchandise sales, home entertainment (DVD, Blu-ray, and rentals), television rights, box office, and licensing deals.

The box office is one of the most critical metrics in the movie industry in evaluating a movie's financial success and future predictions for future revenue releases and streaming releases. This concept describes the total revenue created by a movie's theatrical release. Usually, it is registered in terms of gross box office, which consists of the total ticket sales before any expenses.

The movie industry is an industry that generates millions of dollars per year. A successful movie can create millions of euros in revenue ((Li, 2020), (Terry, Butler, & De'Armond, 2005)) so it is imperative to consider all the factors that can influence box office sales when making a movie. These factors include the quality of the marketing campaign, the movie genre, the time of the year it is released, the release size, the critical reception, and the competition from other movies (Terry, Butler, & De'Armond, 2005). Nevertheless, not all movies are successful and generate millions of dollars (Terry, Butler, & De'Armond, 2005).

In recent decades, streaming services have climbed as an alternative entertainment choice, and their presence has become more significant. Consequently, the box office encountered a decrease in revenue and more competition (Pautz, 2002). Due to the new changes and the vast influence a cinema ticket price has on the financial success of a movie, the companies were guided to adjust movie delivery strategies and pricing strategies to keep up with the new needs and changes.

2.3 Elasticity

The price elasticity of demand determines the percentage shift in the quantity demanded of a product in reaction to a one percent switch in the product's price (Andreyeva & Long, 2010). This measure is frequently used to analyze the relationship between two variables, attendance, and ticket prices, while assessing how receptive customers are to differences in price.

In the cinema industry, the demand for films is susceptible to shifts in price; this means that customers are highly responsive to price alterations. Having responsive customers implies that clients are more willing to acquire tickets at lower prices than at higher prices. Therefore, price increments may lead to a significant loss in attendance and revenue. As a result, companies should be extremely cautious when choosing the optimal price strategy and consider the impact that price changes will have on sales.

In the cinema industry, price elasticity can fluctuate depending on various factors. For instance, customers with access to streaming platforms at a lower cost are expected to reduce the consumption of tickets at elevated prices, or moviegoers are more price-sensitive toward less popular movies than blockbusters.

Due to the environment and nature of the entertainment industry, the company has to optimize its strategies to keep up with the new needs while maintaining profitability and competitiveness. By analyzing and understanding the price elasticity of movie tickets, cinemas can make informed decisions about price strategies while balancing the maximization of attendance levels and revenue.

2.4 Price changes

Price is a crucial element influencing revenue depending on the market circumstances and the industry. In the cinema industry, movie demand is sensitive to price variations (Orbach & Einav, 2007). Furthermore, when the price of a movie ticket changes, the demand from moviegoers will suffer, and consequently, the theatre's revenue will also be affected.

Changes in price influence consumers' behavior and can lead to different reactions (Malc, Mumel, & Pisnik, 2016). Usually, when the consumer is confronted with a price increase in a movie ticket, he will be less incentive to acquire the product. He may look for other alternatives, for example, streaming services. On the other hand, if the price decreases, the consumer's willingness to pay will increase. Customers who were earlier reluctant or incapable of reimbursing a higher price for the product may now be inclined to. They might even acquire a higher quantity compared to the amount obtained at the previous cost. Companies should be careful when varying prices because price changes can damage profits.

The relationship between price and revenue is not constantly forthright in the cinema industry. To deliver the optimal price strategy, theatres must consider several factors and adapt prices accordingly. These factors include the location of the movie theatre, the movie format, the competition landscape, the demand, the time of the day, the day of the week, the quality of the movie, the movie age (whether it is an older title or a new release), movie genre, economic conditions, marketing campaigns (Chang & Ki, 2005); (Walls, 2005); (Zuckerman & Kim, 2003); (Simonoff & Sparrow, 2000); (Litman & Kohl, 1989); (Litman B. , 1982); (Litman B. R., 1983), (Einav L. , 2007), (Sochay, 1994), (Orbach B. Y., 2004), (Orbach & Einav, 2007). Depending on these factors, theatres can practice different prices, for example, higher prices for 3D movies or films with solid marketing campaigns.

The main goal of movie theatres, as any other company, is to maximize their profit; to do so, the company needs to adjust its price strategies to optimize revenue. These changes allow organizations to preserve customer loyalty and maximize revenue while adapting prices based on the consumer's behavior and demand. The movie industry uses diverse strategies, like price discrimination, dynamic pricing, and bundling.

Concluding, the decision to price variations is a highly dedicated act with significant impacts on the industry. When practicing this strategy, the company must consider every consequence and effect that might have on demand and revenues. Decisions like price variations can lead to harmful consequences, such as losses, or, on the other hand, to profit gains.

2.4.1 Dynamic Pricing

Dynamic pricing is one of the most recent price strategies in the cinema industry. Although all movie theatres do not broadly embrace it, its significance has increased recently. This strategy involves changing the product price in real-time established on diverse elements, like time of the day, demand, movie popularity, market conditions, and day of the week (Fernandez, Gerrikagoitia, & Alzua-Sorzabal, 2015), (Kannan & Kopalle, 2001), (Chiang, Chen, & Xu, 2006), (Gibbs, Guttenta, Ulrike, Lan, & Morton, 2018). This approach can produce several procedures, such as:

Demand-based pricing: Consists in the variation of prices grounded on demand for a specific movie. If theatres increase ticket prices for popular movies, it is associated with an increase in revenue. Contrarily, reducing the cost of less popular movies leads to increased attendance, motivating clients to acquire tickets for these types of movies (Shapiro, Drayer, & Joris, 2016). This strategy permits theatres to enhance their income by capturing more value from consumers, reducing congestion, buffing out demand patterns, and increasing room occupancy for non-popular movies.

Time-based pricing: Price changes are found based on the time of day. Movie theatres practice higher prices for peak times and lower prices during off-peak periods to encourage customers to frequent the last period mentioned.

Variable pricing: Movie theatres modify the price of movie tickets based on factors like movie genre, location, and screen size. For example, it is usual to charge higher prices for larger screens, rooms with better sound conditions, and action movies.

Of course, only some things associated with dynamic pricing are beneficial, but the strategy also faces barriers and concerns. The strategy's numerous barriers are the need for more high-tech structures, the small market dimension, and concerns regarding transparency and justice, competition, and consumer behavior.

When applying dynamic pricing in movie theatres, knowing the trade-off between benefits and drawbacks is vital. In addition, to implement this complex strategy, there is a need for investment in algorithms and data analysis instruments.

As mentioned, drawbacks are associated with the negative side of dynamic pricing and, if not controlled or anticipated, can cause tremendous losses to the company. This strategy may cause problems like unpredictability and discrimination due to the lack of transparency, decreased moviegoing experience quality, and attendance. For example, customer attendance and loyalty are based on trust and consequent factors; dynamic pricing based on movie popularity reduces confidence in the approach and is perceived as unfair (Choi & Mattila, 2015).

2.4.2 Price Discrimination

Price discrimination refers to charging special prices to different clients for the same product based on eagerness to pay for a movie ticket. This policy is a common practice employed in the cinema industry in Portugal as well as in the rest of the world. This practice may enhance theatre capacity, improve inventory management, and raise revenue by appealing to more price-sensitive consumers while securing additional returns from clients willing to pay more for movie tickets. There are quite a few methods of price discrimination applied, such as:

Membership-based pricing: Membership programs offer customers access to exclusive or promotional movie tickets, along with rewards points and the advantage of acquiring tickets in advance. The main benefits of this system are to enhance customer loyalty and incentivize the frequency of consumption.

Age-based pricing: To enhance a more inclusive setting and promote consumption, theatres provide promotional prices for seniors, children, and students (Reynolds, 2013).

Location-based pricing: Theatres distinguish prices based on the location, for example, city versus countryside (Forrest, Grime, & Woods, 2000), (Walshe, 1992), (Verhoeff, 1992).

Time and day-based pricing: Depending on the day of the week and the time of the day, cinemas charge different prices for movies ((Orbach B. Y., 2004), (Orbach & Einav, 2007), (de Roos & McKenzie, 2014)).

Bundling: Consists of the discount on movie tickets associated with purchasing additional products or services, like a loyalty program or concessions ((Simon, 1992), (Adams, James/Yellen, & Janet, 1976), (Herrmann, Andreas/Bauer, & Hans, 1996)).

Although price discrimination presents enormous advantages to the industry, it is essential to consider all the concerns raised with this practice. When implementing this policy, it is mandatory to transmit pricing strategies unambiguously and transparently to avoid misunderstandings, hostile responses, and wrong perceptions, like discrimination and unfairness.

2.4.3 Price Bundling

Bundling consists of the concept of price discounts associated with purchasing packages. Thus, acquiring multiple products or services ends up being cheaper than purchasing the same goods offered individually ((Simon, 1992), (Adams, James/Yellen, & Janet, 1976), (Herrmann, Andreas/Bauer, & Hans, 1996)). This strategy is capable of developing various procedures, such as:

Multiple movie tickets: Discounts associated with acquiring various tickets at once. For example, purchasing a collection of tickets for a specific period or movie.

Movie tickets and concessions: Promotional packages comprising movie tickets and concessions (soda and popcorn).

Membership programs: Grant special conditions for members, such as reward points, discounts, the advance of ticket acquisition compared to non-members, and restricted movie tickets.

Price bundling is a commonly used strategy in Portugal due to the benefits it can deliver. The company offers customers increased perceived worth for the same products by bundling goods. As a result, the willingness to pay for the goods separately is less appealing to the client than the package.

The main benefits of this method are prospering the client experience while boosting their loyalty, persuading the acquisition of extra products, simplifying procedures, and growing revenue. However, as with any other price strategy, it is vital to be cautious and aware of its consequences. The stipulation of wrong bundling parameters may appeal to consumers and simultaneously burden the company. The ideal environment is creating bundles of goods that provide extra consumer benefits while optimizing revenue.

2.5 Factors

2.5.1 Channel

The acquisition channel is impactful when analyzing the factors influencing the number of tickets sold and, consequently, the revenue. Movie tickets can be acquired through mobile apps, third parties, box office counters, and online platforms. Movie theatres must identify each channel's impact on the consumer's actions.

The main benefit of mobile and online channels resides in inconvenience; however, other advantages, such as promotions and discounts, are already being promoted on these platforms to increase consumption.

In the last 25 years, several studies have been done regarding how mobile/online payment has become part of society's day and the advantages that come with it.

Mobile payments have been proposed as a key to smooth micro-payments ((Begonha, Hoffman, & Melin, 2002), (Coursaris & Hassanein, 2002)).

There has been a general interest in the use of mobile payment applications ((Dewan & Chen, 2005), (Kreyer, Pousttchi, & Turowski, 2003)). Primarily due to the comfort and simplification of life that they bring. For example, location independence access (Laukkanen & Lauronen, 2005), queue avoidance, and time freedom acquisition.

On the other hand, theatres also provide physical options for consumers who prefer to buy tickets in person, like box office counters.

To provide the best experience to clients and optimize revenues, companies need to understand the effects each purchasing channel has on the demand. Through this analysis, the company can optimize its strategies and make more accurate choices, for instance, where to offer discounts.

2.5.2 Location

To generate substantial revenues, movie theatres need to create thriving movies. They can only achieve this goal if they recognize demographics and regional preferences.

Different countries and regions present distinct cultures, ideologies, and preferences. Hence, when creating movies, theatres must bear in mind all the unique preferences in movies.

Depending on the region of a country, there are clear tendencies regarding demographics. For example, movie theatres in urban areas tend to offer higher attendance and revenue rates than rural ones.

Furthermore, cinemas closer to other movie theatres tend to have lower revenue.

Nevertheless, it is vital to highlight that time is one of the population's most limited resources nowadays. Consequently, time management and safe time are one of their daily priorities.

Although, there are few studies regarding how time-consuming it is to travel to a cinema. In particular, the effect of travel time on cinema visits has not been investigated, and the magnitude of location in demand for theatre has (Forrest, Grime, & Woods, 2000), (Walshe, 1992), (Verhoeff, 1992).

2.5.3 Movie age

The cinema industry is a highly complex and competitive business. Movie age is one of the elements that impact box office revenues. Below are some cases where age is an influencing factor toward gain:

Timing of Release: The release time is crucial when making decisions like movie schedules and marketing campaigns. Movies released through high-demand and less competitive periods tend to perform better than highly competitive and low-demand stages (Brazel & Dang, 2008).

New Releases vs. Older Films: New releases generate more revenue than older movies. New releases can be linked with sensations like thrill, enthusiasm, and novelty. Consequently, the difference in income between the two groups is explained by the absence of these sensations in older movies and their presence in new releases (Orbach & Einav, 2007).

Nostalgia Factor: Through the help of special transmissions and events, older spectators can re-experience memories and feel nostalgic (Kelley, 2014).

Competition from Home Entertainment Options: With the rise of home entertainment options, older films may generate less box office revenue than when fewer home entertainment options were available. Audiences may choose to stay home and watch older movies rather than go to the cinema to watch them.

Home Entertainment Options: With the upsurge of household entertainment choices, like Netflix, older movies may not attract audiences and, consequently, lower revenue levels.

This variable is essential to making informed decisions regarding which movies to screen and when.

2.5.4 Day of the week

In this subchapter, we will explore in which ways the day of the week can influence cinema revenue (Orbach B. Y., 2004):

School Holidays: This period is characterized by the absence of children in school and increased free time. To entertain children, families often choose cinemas as an entertainment activity to occupy their time ((Einav L. , 2007), (Sochay, 1994)).

Weekday: released during the weekdays tend to have lower attendance rates, lower revenue, and worse performance than on weekends. Most moviegoers have more free time on weekends; thus, this group is inclined to go to cinemas on Friday and Saturday nights.

Matinee vs. Evening Shows: Unlike the matinee, evening shows present higher attendance rates and prices. Matinee shows are frequented mainly by people with more free time, like seniors.

Holidays and Special Occasions: During this period, people are more predisposed to go out and celebrate; therefore, there usually is a pick of demand in these periods. Some festivities include New Year's Eve, Easter, Valentine's Day, and Christmas ((Einav L. , 2007), (Terry, Butler, & De’Armond, 2005), (Litman B. R., 1983), (Sochay, 1994), (Litman B. , 1982)).

By understanding these strategies, movie theatres can make informed decisions when choosing staff, schedules, prices, and promotions. Thus, price variation according to the time of the year and the weekday can enhance profits (Orbach B. Y., 2004).

2.5.5 Genre

The variable genre is commonly employed in most studies ((Wallace, Seigerman, & Holbrook, 1993); (Chang & Ki, 2005); (Walls, 2005); (Zuckerman & Kim, 2003); (Simonoff & Sparrow, 2000); (Litman & Kohl, 1989); (Litman B. , 1982); (Litman B. R., 1983)).

Movie popularity can vary depending on the genre since different spectators are interested in distinct genres. Each genre is associated with distinct characteristics that provide clues to the consumer of the content of the movie and help them to retrieve the quality of the movie prior to consumption ((Grant, 2007); (De Silva, 1998)). The succeeding material represents a list of strategies in which genre can influence box office revenue:

Audience Appeal: Different movie genres have different audience appeals. Gender, age, and cultural circumstances are characteristics that tend to affect customers´ preferences toward the movie genre. A practical example is the pattern of females being associated with romantic comedies and males with action.

Marketing: Marketing campaigns vary depending on a movie genre. For example, romantic comedies focus on creating a suspenseful and scary environment.

Competition: Higher levels of competition from other movies in the same genre may influence box office revenue for a specific film.

Box Office Performance: Tendency to perform better than other movie genres in box office metrics.

Pricing Strategies: Higher-demand genres, like blockbuster action movies, tend to present higher prices.

As mentioned, several specialists explore genre's influence in foreseeing revenues (Wallace, Seigerman, & Holbrook, 1993). Some find that only one genre shows a significant effect ((Chang & Ki, 2005), (Sochay, 1994)) or the discovery of two genres (Terry, Butler, & De’Armond, 2005). Others obtain no significant impact of any genre ((Walls, 2005), (Pangarker & Smit, 2013)).

According to the literature review, different experts defend that one specific genre is the one that presents to be more significant. For example, some defend that is science fiction (Litman B. R., 1983), crime (Zuckerman & Kim, 2003), science fiction-fantasy and drama (Litman & Kohl, 1989), comedy and action (Prag & Casavant, 1994), action (Sawhney & Eliashberg, 1996), or thriller and action (Neelamegham & Chinatagunta, 1999).

Creating popular movies, appealing to spectators, and optimizing revenues is neither a direct nor easy job. Companies take a step forward in this direction by leveraging the exclusive attributes of different genres.

3 Experimental Context and Design

3.1 Experimental Context

In partnership with a consulting company, a large movie distributor developed the experiment evaluated in this thesis, referred to as ZOMA. The consulting company oversaw the design, while ZOMA grew the implementation and internal organization. The investigation took place in only one country during July and September 2022.

In 2021, ZOMA was the market leader in the country, with a 50.6% gross revenue market share in movie distribution and a 65% market share in gross revenue in movie screening. ZOMA activities are divided into three "sectors": telecommunications, media and entertainment, and joint ventures. Regarding telecommunications, it offers state-of-the-art mobile and fixed solutions for internet, data, voice, and television for all market segments, precisely enterprise, residential, wholesale, and private.

The media entertainment brunch comprises ZOMA Cinemas and ZOMA Audiovisuals. ZOMA Audiovisuals operates in the audiovisual distribution market while being a leader in the market. Additionally, this branch guarantees the allocation of series and movies by freelance creators and extensive studios for television, film, and audiovisual platforms due to the acquisition and administration of rights.

Lastly, ZOMA has formed joint ventures with strategic allies to leverage the African continent's content enterprise and expansion of operations.

Our study will focus on ZOMA Cinemas, which contains 208 screens distributed nationwide. ZOMA is a leader in national movie screenings and the exhibition of complementary content in cinemas (football, ballet, theatre, concerts, opera, and other events).

ZOMA was the European pioneer to be entirely converted into digital and an innovator employing technologies such as ATMOS, 4DX, IMAX, and XVision.

The movie theatre industry in this country is characterized by highly punctual fluctuations in price across the previous decade and a tiny quantity of operators.

The shutdown and the new regulations that resulted from the COVID-19 pandemic deeply affected the entertainment sector. The Conservancy of constraints (bar consumption, capacity, hourly) and the movie's total closure resulted in an opposing force towards the business.

Besides the existent adversities, external competition, like HBO, Netflix, Amazon Prime, and DisneyPlus jeopardized the movie theater industry during these times.

To defy this challenging period, the corporation digitized procedures, rationalized resources, and evaluated the pricing strategies. Concerning digitization, it is vital to highlight that digital channels stimulate convenience and customer security. In addition, the company also felt the necessity to reassess its pricing strategies.

Our research emphasizes ZOMA Cinemas, a bundle of 30 cinemas nationwide, totaling 210 rooms. Usually, one ticket is purchased for 7,5€; however, depending on the room quality and the type of show, it may vary between 3€ and 15€.

These cinemas transmit mainstream movies and blockbusters such as Top Gun: Maverick, Jurassic World: Dominion, and The Gray Man. Cinemas offer services besides movie tickets; for example, you can reserve a room for a maximum of 20 people for 120€.

The ZOMA cinema delivers different advantages depending on the sales channel and the type of customer. For example, if the client presents ZOMA'S card at the moment of the acquisition, he can get two tickets only for the cost of one ticket, or when purchasing one movie ticket, he will be offered one small menu of popcorn and drink.

3.2 Randomized Experiment / Experimental Setup

We analyze the impacts of a pilot investigation developed by ZOMA **between the 28th of July and the 7th of September**. With this experiment, ZOMA discovered the business level of elasticity; this means ZOMA could observe consumers' reactions and demand for the company's products to price changes on those products.

The company encountered some challenges during the experimental design due to the industry's nature and data. More specifically, the seasonal demand, the elevated volatility, and the substantial performance discrepancy regarding different rooms' typology, capacity, and movie theatres.

Regarding the methodology applied for the pilot experience, ZOMA took a clustering at the level of the room. However, since the 30 movie theatres exhibit significantly distinct seasonal and demographic dynamics, the company could not opt to create clusters at the complex level.

Furthermore, with the help of a density-based clustering algorithm to eliminate outliers and a distance-based algorithm to detect the profiles of the rooms, the company managed to segment the rooms into distinct groups grounded on their profile. During this process, six key demand drivers were identified and employed to find the equivalencies between every single room on all complexes. Within these keys, we have a promotional ticket, the popularity of the complex through the average sale of access, the prevalence of movies with high box office in the room, room capacity, annual seasonality element (focus on August), and average time after the premiere of the sessions of for each movie in the room.

Segmenting group rooms with comparatively homogenous performance was crucial to guarantee balance within all testing groups by contemplating the six chosen tools. With this procedure, the company sought every target group for a specific price shift, including the same number of rooms in each cluster as the other groups.

The objective of this experience was relayed beyond measuring the global influence of price fluctuations, ranging from 10% below the initial price to 10% above that cost. Instead, the company strived to comprehend by what means features like blockbusters, location, and room capacity may attenuate or emphasize the magnitude of those elasticities.

The sample was split into two experimental conditions: treated and control groups. No specific criteria were employed in the division of the parties; however, both groups must present the same composition and conditions. Nevertheless, the two groups were mutually assigned to clusters. The dissimilarity between the groups is whether they suffered from price manipulation. The control group was simply rooms without price deviation. In contrast, the treated group suffered from a price oscillation.

Regarding setups, activation did not summon any interference from the consumer side to access the experience. Likewise, the consumers have yet to receive any notification concerning price shifts. Solely at the time of purchase would they acknowledge the price oscillation. Therefore, transparency was always a value present in any price manipulation.

In addition, the transparency of price shifts was more evident on the app or the site than in the physical box. The final price is automatically displayed on the screen when choosing the ticket in the first procedure. In contrast, the price is exhibited in a price range at the physical box office. Concerning the second method, the client only apprehends the actual value of the ticket at the moment of the payment. Nevertheless, the client always has the choice to continue with the purchase or to give up on it.

Our settings enhance the recognition of the impact of price changes on the consumer's behavior and, consequently, on the company's ticket sales, revenues, and demand by assessing clients in the control group with no price shifting and the treated group with price variation conditions. Therefore, with the information from this experience's results and conclusions, the company can choose the best price strategies to optimize its revenues. Consequently, following the experiment period, some ticket prices of certain cinemas returned to normality, and others were actualized.

4 Methodology and Data

4.1 Sample and timeframe selection

In this subchapter, we will focus on sample and timeframe selection. The methodology chosen to deploy this process is crucial to the generalization and legitimacy of the study outcomes.

In this experiment, the population was the customers who acquired a ticket movie in ZOMA cinemas. On the other hand, the sample consisted of clients who obtained a ticket movie for the clustered rooms during the experiment period.

ZOMA, a large movie distributor in the cinema industry, provided the data chosen. The dataset contained all revenues received in 2022 from all the cinema rooms of ZOMA (population). The population dataset contained 1037801 observations.

The time frame consists of the interval for which the data will be gathered. Intending to deliver the most accurate analysis, precise conclusions and to portray temporal dynamics, the period chosen for the sample was the experimental **period (between the 28th of July and the 7th of September)**.

The choice to emphasize pricing strategies has two leading causes: first, according to economic theory, the competition in the Portuguese movie industry is fearless, and with the climb of streaming services, the movie industry is starting to lose market share. Therefore, the company has to optimize its strategies to keep up with them while assisting the consumer's new and actual needs. Secondly, like any other company, its primary goal is to maximize profit. In this sense, the company must improve its pricing strategies to achieve this goal.

4.2 Data Preparation and Cleaning

The data preparation and cleaning practice was accomplished through the help of the tool RStudio. Firstly, the data was downloaded from Microsoft Excel, where the dataset contained all revenues received in 2022 from all the cinema rooms of ZOMA.

In order to transform raw data into a structured and reliable dataset, the next step was to code and convert the data into a proper format for investigation. All cinema rooms with special conditions, such as ScreenX, Premium, 4DX, IMAX, and XVision, were excluded from the dataset to achieve it. This measure stopped the possibility of misleading guidance for incorrect conclusions.

Subsequently, two vectors were created. One with the treated clusters and another one with the control rooms. Afterward, all the rooms not present in the clustering and, therefore, in the experiment were excluded from our analysis.

Data validation consists of the process of checking inconsistencies and errors. Concerning errors, a total amount of less than 1% of the data presented errors. Some zeros were wrongly misplaced in the revenue and quantity column. To handle it, 0.6% of the data were eliminated from the data set.

Regarding missing data, they were not a topic of interest since the data did not show evidence of any missing data.

The need to calculate derived variables, create new ones, and transform variables arose concerning variable creation and data transformation.

Two variables were generated: Treated and Age. Regarding Age, this variable was formed through the difference in days between the movie's release and the day the ticket was for. The Treated was created as a dummy variable to identify the treatment. This variable assumes the value one when the cinema room belongs to the treatment group and zero when it corresponds to the control group.

Furthermore, two variables were calculated through derived variables. The variable sale price was produced by dividing the gross value of each transaction by the final quantity of each transaction. Additionally, the variable cinema room was generated over the union of two variables, the destination cinema with the room number.

The transformation procedure took place in the variable ticket policy when all the data regarding the ticket policy besides the increase or decrease was erased. This process was also employed in the variable movie premiere date to exclude the extra zeros and transform it into a date format.

Lastly, merge action occurred in the investigation. (Wooldridge, 2013) Panel data is one of applied econometrics's most exploited data structures. A panel set was created to represent the time series for each cross-sectional member in the data set. In this case, a panel set is a collection of data that traces the same variables (genre, channel, age, price, revenue, quantity sold) for the same cinema, per movie and per session rooms over the experience period. With this method, it is possible to study in what manner these variables alter over time for each room and across different cinemas. We can collect knowledge to make informed strategic and financial decisions with this. The panel is unbalanced in this case since some units do not occur in each period.

To conclude, this process enables the data to be categorized as reliable, accurate, and worthy in terms of quality. These high standards guarantee more trustworthy and robust outcomes.

4.3 Model

This chapter focuses on expanding a theoretical framework to instruct this thesis.

The theoretical substance of our research is based on the fixed effects model. This method addresses time-invariant and individual-specific components' effect on the dependent variable while regulating unseen heterogeneity. Since our goal is to explore the effect of variables that change over time and discover the triggers of transformation within an entity (Kohler and Kreuter. 2008).

Accordingly, to (Wooldridge, 2013) when using fixed effects seven assumptions are taken:

Assumption 1:

For each i, the model is

$$y_{it} = \beta_1 X_{it1} + \dots + \beta_k X_{itk} + \alpha_i + \cup_{it}, t = 1, \dots, T$$

where the β_j are the parameters to estimate and $\alpha_i$is the unobserved effect.

Assumption 2:

We have a random sample from the cross section.

Assumption 3:

Each explanatory variable changes over time (for at least some i), and no perfect linear relationships exist among the explanatory variables.

Assumption 4:

For each t, the expected value of the idiosyncratic error given the explanatory variables in all time periods and the unobserved effect is zero: $E(\cup_{it} \mid X_i, \alpha_i) = 0$.

Under these first four assumptions the fixed effects estimator is unbiased.

Assumption 5:

$Var(\cup_{it} \mid X_i, \alpha_i)V = Var(\cup_{it}) = \sigma_{\cup}^2$, for all t = 1, …, T.

Assumption 6:

For all t different from s, the idiosyncratic errors are uncorrelated (conditional on all explanatory variables and α_i): $Cov(\cup_{it}, \cup_{is} \mid X_i, \alpha_i) = 0$.

Under Assumptions 1 to 6, the fixed effects estimator of the β_j is the best linear unbiased estimator.

Assumption 7:

Conditional on X_i and α_i, the $\cup_{it}$ are independent and identically distributed as Normal (0, $\sigma_{\cup}^2$).

Equation *1: Unobserved effects model*

$$y_{it} = \alpha_i + \beta_0 + \beta_1 X_{it} + \cup_{it}$$

Accordingly, to (Wooldridge, 2013) y_{it} is the dependent variable of the entity i at time period t, x_{it} is the line vector $(1 * k)$ that comprises k independent variables pertinent to the understanding of the analysis, β is the column vector of k coefficients to be estimated. Lastly, we have the error term that is divided into two elements. The $\cup_{it}$ is termed as the idiosyncratic error or error term. Represents unobserved factors that change over time and subjects. The α_i consists of the unobserved effect or fixed effect. Captures all unobserved time constant factors that affect the dependent variable and do not change over time.

$\cup_{it}$ is the idiosyncratic error or error term. Represents unobserved factors that change over time and are frequently linked to the covariates. This error term is an individual characteristic that acquires time-constant person heterogeneity.

Regarding the intercept, in the fixed effects model, due to the collinearity with the alpha error, the intercept is dropped.

4.3.1 Regression Models

Four regression models were built on understanding demand and revenue elasticity in the cinema theatre, examining the relationship between the number of tickets sold and price, and revenue and price.

The analysis will be separated into two outcomes (revenue and quantity), each of them with two regressions (a simple and multiple regression).

Model 1 aims to measure and evaluate the relationship between the variable price and revenue in the context of the cinema industry. Model 3 was developed to get a more extensive and profound analysis, where all the covariates in the regression analysis are employed. This model enhances the acquisition of information about the dependent variable (revenue) and the factors that explain it (covariates).

The same reasoning applies to the other outcome (quantity). Respectively, Model 2 comprises of a simple regression model between the quantity sold and the price. Whereas Model 4 comprised the dependent variable (quantity sold) and the covariates.

Equation 2: Model 1

$$\log_{Revenue_{it}} = \alpha_{it} + \beta 1 * \log_{Price_{it}} + \varepsilon_{it}$$

Equation 3: Model 2

$$\log_{Sales_{it}} = \alpha_{it} + \beta 1 * \log_{Price_{it}} + \varepsilon_{it}$$

Equation 4: Model 3

$$\log_{Revenue_{it}} = \alpha_{it} + \beta 1 * \log_{Price_{it}} + \beta 2 * Genre_{it} + \beta 3 * Slot_{it} + \beta 4 * Channel_{it} + \beta 5 * Age_{it} + \beta 6 * Region_{it} + \varepsilon_{it}$$

Equation 5: Model 4

$$\log_{Sales_{it}} = \alpha_{it} + \beta 1 * \log_{Price_{it}} + \beta 2 * Genre_{it} + \beta 3 * Slot_{it} + \beta 4 * Channel_{it} + \beta 5 * Age_{it} + \beta 6 * Region_{it} + \varepsilon_{it}$$

4.4 Variables

This chapter delivers an overview of the crucial elements (variables organized at the cinema room per movie and per session.) analyzed in this research by identifying and describing them.

Table 1: Variables name and description

Variable Name	Description
Movie Genre	The type of genre the movie can assume. This categorical variable includes action, animation, adventure, comedy, drama, terror, and thriller categories.

Channel	Corresponds to the means that took part in the acquisition process of a ticket. This categorical variable can assume the classifications of an app, box office counters, kiosks, web, and self-vending.
Cinema Room	Merge between the cinema name and the room number.
Slot	This variable is divided into five categories that correspond to the period of the day the ticket is acquired. It can adopt the values of opening, morning, midnight, afternoon, and night categories.
Destination Cinema Region	Corresponds to the region where the cinema is located. This categorical variable can assume the categories of Center, Grande Lisboa, Grande Porto, North, South, and Madeira.
Total Gross Value	The total amount in euros of revenue generated by a specific cinema room on a specific day.
Total Net Value	Total liquid revenue in euros produced for a specific movie in a specific cinema room in a specific timestamp.
Average Sale Price	The average rate charged per ticket.
Treated	Assumes the value one when the cinema room has received treatment and takes the value zero when it belongs to the control group.
Average Age	Average number of days that the film has since its release.
Average Week	Average week number.
Start	Date of the session composed by day, month and year.

5 Results analysis

A concise review of the descriptive statistics and graphical analysis of the critical covariates incorporated in the econometric model was conducted before proceeding to any regressions.

5.1 Summary statistics

I conduct a preliminary analysis in this subchapter while contextualizing the numeric results according to the thesis topic.

Table 2 shows summary statistics for each cinema room, per movie and per session. This table delivers the descriptive statistics for the primary variables studied in our analysis during the experimental period. From our random sample 1037801 observations, only around 1,45% (15018) of the data was incorporated into the experiment.

Additionally, on average, each cinema room, per movie and per session sold a total amount of tickets valued at 30.65€. Revenue ranges from approximately 3.6€ to 681.81€, with a standard deviation value of approximately 38.56€, pointing to a high level of variability and spread.

Approximately, on average, five tickets were purchased for each cinema room, per movie and per session , with an average expenditure of 5.77€ per ticket. However, on average, ticket prices ranged between 7.81€ and 1.8€.

According to the summary statistics (See table 2), more than half of the observations suffered from price manipulation during the experiment. In other words, on average, 76.5% of the observations belonged to the treated group and 23,5% to the control group.

Table 2: Summary Statistics per cinema room, per movie and per session

	N	Mean	St. Dev	Min	Max
Total sold Tickets	15,018	5.404	6.809	1	108
Total Gross Value	15,018	30.652	38.563	3.600	681.810
Total Net Value	15,018	28.922	36.383	3.396	643.217
Average Sale Price	15,018	5.765	0.756	1.800	7.810
Treated	15,018	0.765	0.424	0	1
Average Age	15,018	26.936	24.378	1.000	107.000
Average Week	15,018	32.525	1.647	30	35

5.2. Graphical analysis

Figures 3 and 4 represent the frequency distribution of revenue level and log, respectively. The level plot shows that the distribution is right/positively skewed. Pointing that almost all the values are located on the left side of the graph (long tail on the left side), around the value zero. As can be observed, values higher than 400€ of revenue are absent. Regarding the outliers, values higher than 200€ are considered outliers. We can observe that logging revenue generates a less skewed dependent variable. Furthermore, as displayed in the summary statistics table (table 2), this variable is permanently positive. Consequently, employing the log of the variable will facilitate the analysis of the projected regression coefficients.

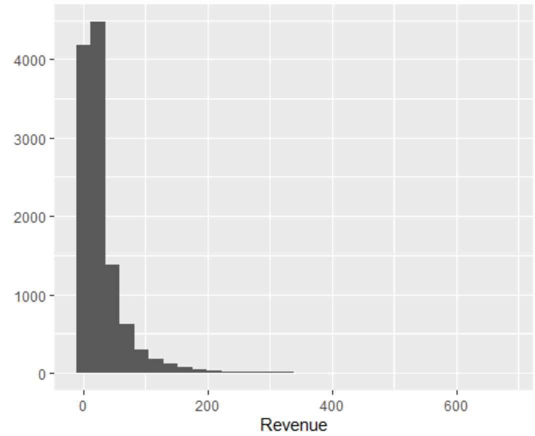


Figure 3: Revenue distribution

Figure 4: Log revenue distribution

Fig.5 displays the graphical representation of the revenue distribution for the different ticket policies: +10%, +7.5%, +5%, -10%, -5%, 99c, and Control Group.

This instrument facilitates spotting the dispersion of the data set rapidly, the median score of a data set (mean value), and markers of skewness. The boxes present evidence of asymmetry. However, each type of policy presents a different form of asymmetry. In Figure 5, most policies present a positively skewed (skewed to the right).

In a box plot, the median is represented by the line that separates the box into two parts.

The group with an increment of 10% in the sales price presents the highest median value, followed by an increment of 5%. Therefore, the policy of +10% creates the highest revenue among the policies.

In contrast, the ticket policy with the lowest average value was a decrease of 10% of the ticket price. Concluding, given a specific policy, the average is likely to be distinct from the remaining policies.

An outlier consists of a data point that can be found outside the box-and-whisker plot. Additionally, each ticket policy presents outliers in this box plot's upper extreme (higher values). Policy 99c shows higher values of outliers in comparison with the other policies.

Regarding dispersion, the smaller the box, the less spread the data is, and vice-versa.

However, the difference in the length of each box is not significant when comparing them.

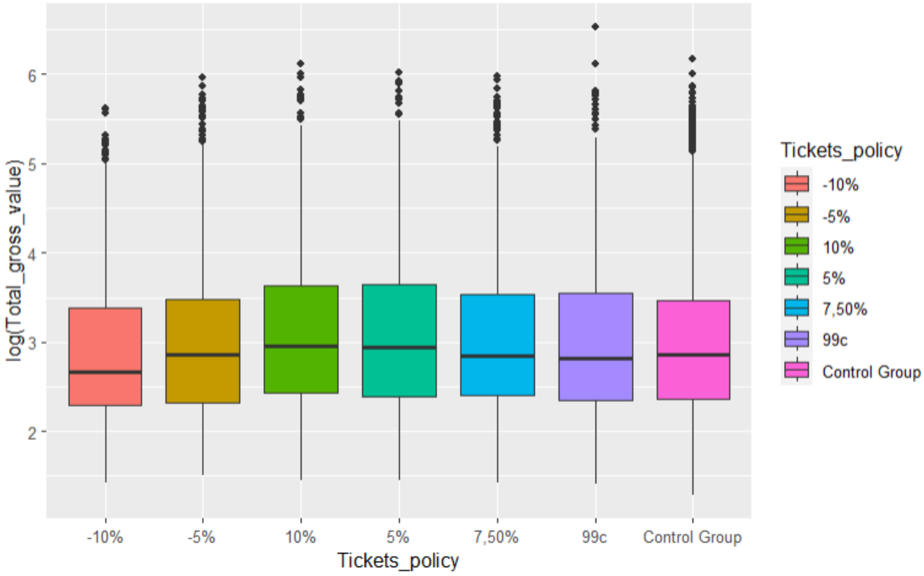


Figure 5: Boxplot of log revenue per ticket policy

Figure 6 presents the relationship between Logged Revenue and Sales, showing a positive non-linear relationship between the two variables.

This outcome is aligned with the conclusions extracted from the literature review.

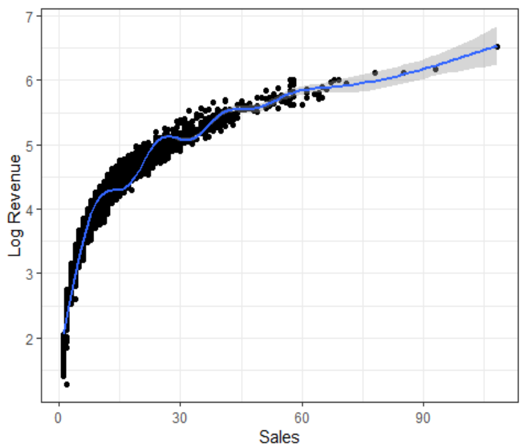


Figure 6: Relationship between log revenue and sales

5.3 ANOVA

In this section, I present the results and investigation from a one-way analysis of variance (ANOVA). The main goal of the one-way ANOVA is to assess the impact of different ticket policies on revenue and the impact of different ticket policies on the quantity of sold tickets.

5.3.1 One-way ANOVA

Assess if the type of ticket policy applied affected the final revenue:

Table 3: One-way ANOVA between revenue and ticket policy

	Df	Sum Sq	Mean Sq	F-value	Pr(>F)
Tickets Policy	5	55	11.069	15.29	5.23e-15***
Residuals	11482	8313	0.724		

In Table 3, the p-value of the ticket policy variable is low (p-value < 0.001). Therefore, the null hypothesis of equality of all means at the 1% level of significance is rejected. Therefore, the mean revenue generated by the distinct policies are different.

Signif. codes	0 '***'	0.001 '**'	0-05 '*'	0.1 '.'	1 ' '

Evaluate if the type of ticket policy applied affected the final quantity of tickets sold:

Table 4: One-way ANOVA between quantity sold and ticket policy

	Df	Sum Sq	Mean Sq	F-value	Pr(>F)
Tickets Policy	5	4	0.8698	1.172	0.32
Residuals	11482	8518	0.7419		

As shown in Table 4, the p-value of the ticket policy variable is high (p-value >0.05), so the type of ticket policy does not present a tangible impact on the final quantity sold.

5.4 Regression Analysis

The last stage of this chapter focuses on creating the best regression model possible to understand revenue elasticity in a cinema theatre, examining the relationship between revenue and the independent variables and the connection between the number of tickets sold and the covariates. The variable selection was based on intense economic theory research from the data's descriptive statistics and existing models with similar objectives.

5.4.1 The Effect of Price on Revenue

Model 1 aims to measure and evaluate the relationship between the variable price and revenue in the context of the cinema industry. Thus, the analysis contributes to investigating price contribution in forecasting revenue while simultaneously evaluating the impact of price changes on revenue. Furthermore, in order to get a more extensive and profound analysis, another model was created. The third model employs all the covariates in the regression analysis to acquire more information about the dependent variable (revenue) and the factors that explain it (covariates).

The second model will measure, evaluate, and acquire more knowledge sources involving the relationship between the price and the total number of tickets sold (quantity) in the context of the cinema industry. On the other hand, the fourth model was built to acquire more information encompassing the impacts of covariates exhibited on the dependent variable (quantity of tickets sold).

Subsequently, the following linear models will be estimated:

Table 5: Regression Results

	Dependent variable:			
	log(Total_gross_value) (1)	log(Total_sold_tickets) (2)	log(Total_gross_value) (3)	log(Total_sold_tickets) (4)
log(Average_sale_price)	-0.163**	-1.159***	-0.176***	-1.170***
	(0.071)	(0.075)	(0.065)	(0.066)
Movie_genreAdventure			-0.060**	-0.059**
			(0.029)	(0.029)
Movie_genreAnimation			0.170***	0.175***
			(0.024)	(0.025)
Movie_genreComedy			0.114***	0.115***
			(0.027)	(0.027)
Movie_genreDrama			0.031	0.033
			(0.042)	(0.042)
Movie_genreTerror			0.020	0.022
			(0.059)	(0.060)
Movie_genreThriller			-0.192***	-0.192***
			(0.036)	(0.036)
SlotMidnight			-0.265***	-0.267***
			(0.028)	(0.029)
SlotMorning			-0.505***	-0.507***
			(0.051)	(0.051)
SlotNight			0.024	0.023
			(0.018)	(0.018)
SlotOpening			-0.501***	-0.504***
			(0.025)	(0.025)
ChannelKiosk Selfvending			0.033	0.032
			(0.032)	(0.032)
ChannelPhysical Ticket Office			0.662***	0.663***
			(0.020)	(0.020)
ChannelSelf-vending			-0.029	-0.031
			(0.038)	(0.038)
ChannelWebticket			0.132***	0.131***
			(0.025)	(0.025)
Average_age			0.002***	0.002***
			(0.0004)	(0.0004)
Observations	11,488	11,488	11,488	11,488
R2	0.0005	0.023	0.168	0.186
Adjusted R2	-0.008	0.015	0.160	0.179
F Statistic	5.291** (df = 1; 11394)	266.066*** (df = 1; 11394)	143.571*** (df = 16; 11379)	162.986*** (df = 16; 11379)

In model one, the logged price coefficient presents a value of minus 0.163. This coefficient measures, on average, the expected percentage customers spend every time the ticket price increases by 1%. Because the coefficient is an elasticity, a 1% increase in the ticket price is predicted to decrease revenue by 0.163%, ceteris paribus. It is significant at the 5% level, denoted by the two stars symbol after the coefficient. Concerning the covariant of interest – Price –presents an inverse/negative relationship with revenue. Thus, revenue tends to decrease in the presence of price raises.

Regarding the third model, the logged price coefficient presents a value of minus 0.173, whereas the variable age presents a positive coefficient of 0.2002001 (exp(0.002)-1)*100). The price coefficient measures, on average, the expected amount customers spend every time the ticket price increases by one euro, ceteris paribus. Since the coefficient is an elasticity, a 1% increase in the ticket price is predicted to decrease revenue by 0.176%, ceteris paribus. It is significant at the 1% level, denoted by the three stars symbol after the coefficient.

The age coefficient measures the average expected revenue variation associated with an increase by one day that the film has since its release, ceteris paribus. A one-day increase in age increases predicted revenue by approximately 0.2 percent, ceteris paribus. The three stars located next to the factor designate that this value is statistically distinct from zero at the 1% level (α = 0.01).

As the literature review suggests, the older the movie is, the less revenue is associated with that movie. This information can be corroborated with the observed model since the increase in revenue is very small (lower than one percent) the older the movie is.

Nevertheless, the coefficient for genre terror, genre drama, slot night, channel self-vending, and channel kiosk self-vending are statistically insignificant, which implies we cannot reject the hypothesis that it is not substantially distinct from zero, even at the 10% significance level.

This regression model's primary outcomes align with the conclusions extracted from the literature review.

R-squares is a goodness-of-fit measure for linear regression models. The model presents an R squared in the value of 0.168. This value reveals that the regression model explains 16.8 percent of the variability detected in the target variable (revenue).

In the second model, the variable price presents a negative coefficient of 1.159. This coefficient measures, on average, the expected amount customers spend every time the ticket price increases by one euro. Since the coefficient is an elasticity, a 1% increase in the ticket price is predicted to decrease revenue by 1.159%, ceteris paribus. It is significant at the 5% level, denoted by the two stars symbol after the coefficient.

The model presents an R squared in the value of 0.023, meaning that the independent variable (total average price) can explain 2.3 percent of the variance of the dependent variable (total sold tickets).

The primary outcomes from the model are aligned with the literature review. Both knowledge sources exhibit an inverse/negative relationship between price and quantity sold; thus, quantity sold tends to decrease when the price increases.

On the other hand, the two sources support the significant influence price variations have on the number of tickets sold in the cinema industry. The null hypothesis is rejected since the p-value is lower than 0.05; therefore, a price increase is negatively linked with the number of tickets sold.

The last model delivered a negative price coefficient with a value of 1.170, whereas the variable web ticket presents a positive coefficient of 13.99678 (exp(0.131)-1)*100).

The price coefficient measures, on average, the expected amount of tickets sold every time the price varies by one euro, ceteris paribus. Since the coefficient is an elasticity, a 1% increase in the ticket price is predicted to decrease quantity by 1.170%, ceteris paribus. This value is statistically distinct from zero at the 1% level (α = 0.01).

On average, all else constant, consumers who purchase tickets through the web ticket buy approximately 14 percent more than customers through the app, ceteris paribus. It is significant at the 1% level, denoted by the three stars symbol after the coefficient.

The literature review can corroborate this regression model's primary outcomes.

Nevertheless, the coefficient for genre terror, genre drama, slot night, channel self-vending, and channel kiosk self-vending are statistically insignificant, which implies we cannot reject the hypothesis that it is not substantially distinct from zero, even at the 10% significance level.

R-squares is a goodness-of-fit measure for linear regression models. The model presents an R squared in the value of 0.186. This value reveals that the regression model explains 18.6 percent of the variability detected in the target variable (quantity sold).

6 Conclusion

The main goal of movie theatres, as any other company, is to maximize their profit; to do so, the company needs to adjust its price strategies to optimize revenue. Due to the environment and nature of the entertainment industry, the company must be extremely careful when adapting prices based on the consumer's behavior and demand in order to preserve customer loyalty and maximize revenue.

This thesis has emphasized the complex nature of price elasticity contained by the cinema industry. This industry is not a fixed parameter, the opposite it changes in reaction to movie age, genre, channel, price, location.

The primary outcomes from the models are aligned with the literature review. Both knowledge sources exhibit an inverse relationship between price and quantity sold; thus, quantity sold tends to decrease when the price increases.

As mentioned, the cinema industry is highly complex and competitive. Movie age is one of the elements that impact box office revenues. New releases generate more revenue than older movies. New releases can be linked with sensations like thrill, enthusiasm, and novelty.

As can be observed in the models and corroborated by the literature review, the older the movie is, a very small increase in the quantity of sold tickets is observed.

In the last 25 years, several studies have been done regarding how mobile/online payment has become part of society's day and the advantages that come with it.

Mobile payments have been proposed as a key to smooth micro-payments ((Begonha, Hoffman, & Melin, 2002), (Coursaris & Hassanein, 2002)). As can be detected in the models on average, all else is constant, consumers who purchase tickets through the web ticket buy approximately more than customers through the app.

To conclude, these findings contribute to expanding the knowledge inside the cinema industry. The results from this study will be a worthy resource not only inside the cinema industry but also for future analyses regarding consumer actions, dynamic prices, and the decision-making process of other industries.

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