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RESEARCH ARTICLE

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Sunk Cost Fallacy, Price Adjustment, and Subscription Services for Information Goods

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Abstract

Information goods often adopt a subscription-based business model, where customers pay a fixed fee to enter into a purchase agreement. The up-front payment of the subscription fee creates a sunk cost for members, which may influence their future consumption behavior. Although price adjustment is a common strategy employed by subscription providers, it remains unclear how changes in the fixed fee—as a sunk cost—affect the consumption of information goods. For this paper, we first leveraged a quasi-natural experiment in a movie subscription service and employed a difference-in-differences model to estimate the impact of fixed fee adjustments on overall consumption. Then we used a randomized experiment to unveil the underlying mechanism of sunk cost fallacy. Our findings reveal that the average treatment effect on information goods consumption is both significant and economically meaningful. Specifically, the box office revenues of an average movie increased by 12%~35% in the six months following a sudden downward price adjustment, likely because a lower fixed subscription fee appeals to highly price-conscious consumers, who are more susceptible to the sunk cost fallacy. We also uncovered insightful heterogeneous effects, demonstrating that niche information goods, especially those driven by narrow appeal and high quality, benefit the most from such a downward price adjustment of a subscription service. Our results are robust to alternative control groups, placebo tests, and different data analysis granularity. Our research enhances the understanding of the sunk cost fallacy within the context of subscription-based information goods.

Keywords: Subscription Service, Sunk Cost, Price Adjustment, Quasi-Natural Experiment, Niche Information Goods

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1 Introduction

Subscription-based commerce has grown rapidly in recent years, driven largely by online services (McCarthy et al., 2017). It delivers a flow of goods or services directly to customers in exchange for a periodically recurring fee (Taylor, 2003). According to a McKinsey survey (Chen et al., 2018), about half of US consumers use at least one subscription-based service, with over 35% of them using three or more subscription services. Though previously dominated by newspapers, magazines, and health & beauty products, digital disruption and technological advancement have led to the increased use of subscription-based services for information goods, such as television and movie streaming (e.g., Netflix), online video games (e.g., Xbox Game Pass), music streaming (e.g., Spotify), software as a service (SaaS), and subscription-based software licensing (e.g., Tableau, Microsoft Office).

Subscription services for information goods typically employ a nonlinear pricing strategy, which involves setting a fixed fee for customers to enter into a purchase agreement (Ho & Zhang, 2008). Normative economic theories suggest that the up-front fees should not be taken into account when making subsequent consumption decisions. However, behavioral economic theories propose that individuals may exhibit the sunk cost fallacy, meaning that the irrecoverable payment could significantly impact their future consumption levels (Iyengar et al., 2022). The degree of sunk cost bias may be influenced by the size of the fixed payment (Arkes & Blumer, 1985), creating a crucial link between a firm's pricing decision and the overall consumption level.

To remain profitable and attract subscribers, providers of subscription-based information goods often adjust their fixed fees. The profitability of such a subscription program is contingent on whether the increase in revenue outweighs the additional cost. While the marginal cost for most subscription-based information goods is nearly zero (e.g., Netflix), new subscription models have emerged that have subverted this premise. For example, subscription-based movie ticketing offerings may incur additional costs due to the capacity constraints of movie theaters, and third-party subscription providers may need to pay additional license fees due to increased consumption. Thus, a variation in the pricing of fixed fees for information goods can impact both revenues (i.e., related to the number of subscribers and subscription fee) and costs (i.e., positively related to consumption), which heavily depends on the resulting variation in consumption level. More specifically, subscription providers should avoid overconsumption in their attempt to stimulate subscription volume through price adjustment strategies. Therefore, understanding how the price adjustment of fixed-fee subscriptions affects the consumption of information goods is of great interest to subscription providers.

However, whether providers can reap benefits from price adjustment strategies is uncertain, as how the reduction of up-front fees affects consumption is not yet conclusive. First, the nonrefundable up-front fee serves as a sunk cost, which may encourage irrational consumption behaviors among subscribers. Some literature has argued that the magnitude of past payments positively correlates with susceptibility to the sunk cost fallacy (Arkes & Blumer, 1985), suggesting that a reduction in up-front fees might reduce the tendency to consume information goods. Yet, the findings about how sunk costs impact decision-making remain fragmented (Roth et al., 2015)—for example, the above viewpoint has been challenged by the concept of "relative sunk cost" (Garland & Newport, 1991), which posits that the decisive factor is not the absolute size of a monetary investment but rather its proportion to the total budget.

Second, prior studies on sunk cost have predominantly focused on the impact on individuals' decision-making through experimental approaches under hypothetical scenarios such as project investment, leaving the subscription context in marketing practice in terms of aggregate consumption levels largely overlooked. Conventional sunk cost scenarios are typically categorized into two decision types: utilitarian or progress (Roth et al., 2015). Utilization decisions involve a scenario where a decision maker faces two equally attractive alternatives, with preferences shifting toward the one alternative involving a sunk cost. Progress decisions occur when a decision maker allocates additional resources to an option initially selected, such that the sunk costs increase the likelihood of further fund allocation. Our context of information goods subscription is different from these established categories since consumers do not need to make choices and the marginal price of information goods is zero (i.e., no additional fund allocation). Thus, prior findings about how sunk costs impact individuals' behaviors are not directly applicable herein.

Third, the heterogeneity of sunk cost bias has not been sufficiently explored. In marketing practice, it is crucial to consider different consumer segments since they may respond differently to a firm's pricing strategies (Palazón & Delgado, 2009). A reduction of the up-front fee can lead to a shift in the composition of the user base. A lower up-front fee is likely to attract highly price-conscious consumers who would invest much time searching for a lower price (Lichtenstein et al., 1993). Such consumers typically have lower opportunity costs of time and are more susceptible to the monetary sunk cost. Hence, we propose our research question: *How does the adjustment of up-front fee—as a sunk cost—affect the consumption of information goods?*

To answer our research question, we leveraged a quasi-natural experimental opportunity in a typical information goods setting, i.e., the movie exhibition industry. In particular, we focused on a start-up company MoviePass, which provides subscription-based movie ticketing services. It is operationalized through a geolocation-based smartphone app and allows a subscriber to attend a specific number of movies per month for a monthly fixed subscription fee. On August 15, 2017, MoviePass suddenly implemented a significant downward price adjustment strategy without any advanced announcement. It dropped the fixed fee from \$50 to a much lower price of \$9.95 (Buckley, 2018). Since MoviePass is a third-party provider with no direct relationship to movie exhibition or production companies, it provided a great opportunity to quantify the impact of price adjustment of subscription fees on overall movie consumption (i.e., box office revenue). Furthermore, we conducted a post hoc experiment to verify our proposed mechanism of sunk cost fallacy in a more straightforward way by directly measuring individuals' price consciousness and susceptibility to sunk costs.

Our empirical results generate some intriguing insights. We demonstrate that the downward price adjustment of the subscription fee had a substantial effect on driving overall consumption. It extends our understanding of the sunk cost fallacy such that different individuals may have different susceptibilities to this bias. Consistent with our conjecture, our results suggest that when the fixed fee is adjusted to a lower level, the subscription service attracts customers who are highly price-conscious and are more susceptible to the sunk cost fallacy, leading to an escalation of commitment manifested as increased consumption. Furthermore, despite the above-mentioned impact being amplified for low-popularity information goods, further granular analyses show that the impact on the consumption of low-popularity goods is only significant if the low popularity is driven by narrow appeal and high quality. Different from prior literature assuming that highly price-conscious consumers are exclusively focused on products' prices while being likely to ignore the quality values, our results indicate that quality does matter, even for highly price-conscious customers. These findings suggest that high-quality and niche information goods may benefit from such a price adjustment strategy, thus leading to a more fragmented market. It may also assist subscription service providers in designing more efficient price adjustment strategies.

The remainder of this study is organized as follows. In Section 2, we review the prior literature on subscription services, price adjustment, and the sunk cost fallacy. In Section 3, we develop our hypotheses, and in Section 4, we describe the research context and dataset. Section 5 describes our identification strategy and model specification. Sections 6 and 7 present the main empirical results and robustness checks. Section 8 demonstrates our post hoc experimental study, which tested the underlying mechanism in a direct manner. Section 9 concludes with a discussion of the theoretical contributions, practical implications, limitations, and directions for future research.

2 Literature Review

2.1 Subscription Services of Information Goods

With the advancement of information technology, there is an increasing trend of subscription-based services for information goods, such as streaming television and movies (Yu et al., 2022), music (Aguiar & Waldfogel, 2018), and software (Zhang & Seidmann, 2010). This stream of research mainly examines how subscription-based services affect product sales or consumer demand. However, the findings are inconclusive. For instance, Aguiar and Waldfogel (2018) demonstrated that subscription-based streaming services lead to reductions in sales of recorded music. Similarly, Yu et al. (2022) found that online subscription services cannibalize physical sales. Conversely, Kretschmer and Peukert (2020) showed that enabling access to online streaming services will stimulate sales of the artist's albums. Similar findings were revealed by Datta et al. (2018), suggesting that the adoption of subscription-based streaming services leads to long-term growth in overall music consumption. More interestingly, researchers have also verified that subscribing to video streaming services can curtail digital piracy (Aguiar & Waldfogel, 2018; Lu et al., 2021), which may indirectly trigger the increase in legal product sales.

Different from the above-mentioned subscription services, a new subscription model has emerged that offers services from different offline sellers/vendors to variety-seeking consumers through an online platform (Gal-Or & Shi, 2022). It differentiates itself from traditional subscription-based streaming services (e.g., Netflix) with two unique features. First, it acts as an intermediary third-party platform that offers members access to the service providers' content at a fixed price. Second, it primarily operates within an online-to-offline framework, where the services are delivered offline, but the digital subscription platform integrates these services, providing customers with the flexibility to choose among different sellers. These differences pose fundamental challenges to our previous understanding. For consumers, there are additional transportation and time costs when nearby service providers are limited, leading to higher uncertainty on the demand side. For the subscription platform, the marginal cost of consumption may be significant, as it may incur additional costs due to the capacity constraints of physical locations and the need to pay licensing fees to service providers. In this regard, the subscription platform should carefully manage consumption levels while trying to stimulate subscribers.

Researchers have shown a growing interest in this type of subscription service, particularly in exploring the strategic interaction between the intermediary subscription platform and the service provider. By proposing a game-theoretic model, Dey et al. (2020) answered the question of when service providers should cooperate with (or compete against) the intermediary subscription platform. Li et al. (2020) presented analytical models to compare the pricing approach in the intermediary subscription platform with the conventional per-use pricing approach. Gal-Or and Shi (2022) further discussed which markets best fit this business model and investigated which type of agreements between platforms and sellers can sustain the model. Despite its popularity, stylized analytical studies dominate, while empirical studies are scarce. These studies focused primarily on how to reach agreements between the involved two parties, discussing critical negotiation variables such as quality of service, variable fee per customer served, seller total capacity, and platform revenue share. A consensus has been reached that the negotiations have to ensure that the subscription service yields mutual benefits for both platforms and service providers. However, existing studies have tended to overlook the platforms' subsequent post-negotiation strategies, which are independent of the sellers and still significantly affect their profits. Specifically, the interactions between intermediary platforms and consumers, especially how platforms' independent post-negotiation pricing strategies affect consumption levels, remain underexplored. Given the distinctions from traditional subscription models mentioned above, prior findings on how subscription services impact consumption do not apply here. This research gap motivated our study.

2.2 Price Adjustment of Subscription-Based Services

Subscription-based services typically adopt periodic, pre-paid, flat fees, and impose quotas restricting the maximum consumption levels (Sun et al., 2006). A set of goods or services is offered as a package to the consumer, usually at a lower price than a separate purchase (Schlereth & Skiera, 2012; Schlereth et al., 2010). Researchers suggest that such prepaid arrangements transform deal-by-deal transactional relationships into contractual relationships. Under such scenarios, consumers are unsure about their future consumption needs, introducing uncertainty into their decision process (Chen et al., 2020; Shugan & Xie, 2000; Sun et al., 2006). In terms of how subscription-based fixed fee pricing affects the revenue of information goods, prior studies have reported inconclusive findings (e.g., Kretschmer & Peukert, 2020; Yu et al. 2022). This suggests that unpredictability in demand may translate into revenue uncertainty.

Regarding efforts to boost revenues, researchers have begun to examine the optimal pricing of subscription-based services, revealing that platforms can offer differentiated prices to different types of consumers (e.g., DeValve & Pekeĉ, 2022). Kao et al. (2020) generally proposed that the intermediary subscription platforms should utilize the usage data of customers to learn their preferences and adjust their subscription prices to earn more profit. Kumar and Sun (2020) verified this, finding that customizing the subscription prices in accordance with the service time can help reap more benefits. Using an analytical modeling approach, Mai and Hu (2023) derived that the optimal subscription price can initially be high and then decrease gradually. In particular, optimal prices of service subscriptions have been shown to align with the willingness to pay for lower-type customers (Wang et al., 2019). DeValve and Pekeĉ (2022) differentiated high-disutility consumers from low-disutility ones and showed that competition increases subscription prices more for the former than the latter. Further, some studies have explored why price adjustments of subscription services occur. Pattabhiramaiah et al. (2018) examined why newspaper publishers increase subscription prices given declining trends of demand. They rationalized this phenomenon by revealing the decline in publishers' ability to subsidize readers. From an opposite perspective, Brecko (2023) examined why software firms are less likely to increase subscription prices for the latest versions. This study revealed that high-value, price-insensitive consumers do not value new versions, making it less profitable to make price adjustments.

Although prior studies have begun to explore price adjustment for subscription-based services, most of them have focused on the optimal pricing strategy from the standpoint of firms, primarily using analytical modeling approaches. Scant empirical evidence has directly uncovered how and why subscription fee adjustment can affect consumption from the viewpoint of consumers.

2.3 Sunk Cost Fallacy

Our work is related to the extensive literature on how sunk costs affect decision-making. Sunk costs are irrecoverable investments that do not affect the incremental payoffs of future decisions; hence, they should play no role in rational decision-making (Arkes & Blumer, 1985; Sweis et al., 2018). Nevertheless, the sunk cost fallacy arises because it poses a psychological cost and individuals tend to change their behavior to offset the psychological burden of the cost (Ho et al., 2018; Iyengar et al., 2022; Thaler, 1980), often referred to as the "irrational escalation of commitment" (Friedman et al., 2007; Keil et al., 2000b). Several studies have found that people exhibit sunk cost fallacy in various scenarios, including R&D expenditures (Hong et al., 2019; Keil et al., 2000a), season tickets (Arkes & Blumer, 1985), car usage (Ho et al., 2018), and MOOC (massive open online course) engagement (Goli et al., 2022). For example, the mere act of paying for a course can increase users' engagement with course content (Goli et al., 2022). Iyengar et al. (2022) studied the sunk cost effect in subscription programs offering beauty care products and found that the up-front subscription fee creates a sunk cost and induces customers to increase their future purchases so that they can utilize the program benefits and recover the initial payment.

Although most research focuses on the impact of sunk costs on individual decision makers, scholars have also investigated the interplay between firms' pricing strategy and the sunk cost bias. For instance, Wang and Yang (2010) examined how the sunk cost effect resets a monopolistic firm's optimal two-part pricing, showing that the sunk cost effect of an up-front fixed fee gives the firm an incentive to raise the unit price and increase the market coverage by charging a lower fixed fee. Jain and Chen (2022) found that sunk cost bias can sometimes alleviate self-control problems and lead to higher profit for the firm as well as higher social welfare.

Zhang et al. (2021) compared fixed-fee contracts that induce the sunk cost fallacy with pay-per-use contracts that do not, aiming to design an optimal contract. Our work is different from this stream of research in three ways. First, most studies have applied analytical modeling approaches and focused on examining optimal contractual design among several common contracts such as pay-per-use, fixed-fee, and two-part contracts without exploiting the details of each contract. For this paper, we instead studied the variation of one specific contract, that is, the price adjustment of a fixed-fee contract, and conducted an empirical study exploring how it impacts consumption via the sunk cost fallacy. Second, existing research tends to investigate how firms react to consumers' sunk cost bias from the perspective of firms such as their pricing decisions, product design, and advertising strategies, while there is a lack of studies from the opposite angle, i.e., studies exploring how aggregate consumption patterns respond to firms' pricing strategies from the standpoint of consumers. Third, prior studies have neglected the fact that certain consumer characteristics might be associated with the magnitude of the sunk cost fallacy they suffer. We considered a feature that is closely intertwined with firms' pricing strategy—consumers' price consciousness—to identify consumer segments that are more susceptible to the sunk cost fallacy.

The effect of sunk cost is not a one-size-fits-all framework and the literature has investigated various factors that can strengthen or attenuate the sunk cost fallacy. The primary finding is that the size of past payments has a positive relationship with the sunk cost fallacy (Arkes & Blumer, 1985). For instance, customers who initially paid more for a season subscription tend to attend more plays. However, this viewpoint has been challenged by the concept of "relative sunk cost," which is defined as the percentage of the total budget already spent (Garland & Newport, 1991). That is, individuals are more likely to persist in a course of action when the payment takes up a higher proportion of their overall budget. Further, Gourville and Soman (1998) found that the sunk cost effect is transient and is dependent on the recency of payment. People gradually adapt to their upstream transaction cost over time, thus diminishing the sunk cost effect on their further consumption decisions. Taking advantage of this "payment depreciation," Hafenbrack et al. (2014) suggested that the sunk cost fallacy can be attenuated by drawing one's temporal focus away from the future and past. Another important but relatively overlooked research stream is how individuals differ in their sensitivity to sunk costs. For example, women are more likely to regret emotion than men (Li et al., 2018); more experienced people have less intense endowment effects, which are related to the sunk cost fallacy (List, 2003); a negative correlation between age and susceptibility to the sunk cost fallacy has been documented (De Bruin et al., 2014); and people with lower income are more likely to make errors in economic reasoning, including falling prey to the sunk cost fallacy (De Bruin et al., 2007). However, most previous studies have focused on demographic characteristics to explore user heterogeneity in individual decision-making within a psychological research paradigm with hypothetical scenarios. The factors that are related to the marketing practice, particularly at aggregate-level outcomes such as consumption patterns, remain relatively unexplored. Thus, there is still much room to discuss consumer segments that are more likely to exhibit the sunk cost fallacy. Against this backdrop, we add to this literature by focusing on consumers' consciousness of the firms' pricing strategy and their susceptibility to the sunk cost, thus enhancing our understanding of consumer behavior in terms of both the consumption level and variety.

3 Hypotheses Development

The subscription-based pricing model is a popular strategy for pricing information goods, allowing firms to take advantage of their low marginal costs (Fishburn et al., 2000). Specific pricing schemes include a two-part tariff (Schlereth et al., 2010; Wu & Banker, 2010), a three-part tariff (Lambrecht et al., 2007), and bucket pricing (Schlereth & Skiera, 2012), among which the fixed fee is a crucial component for the initial allowance. For customers, the up-front fixed fee payment tends to be perceived as a loss and the subsequent consumption of information goods as a gain (Ho & Zhang, 2008). As such, consumers benefit more from the subscription service when they consume more.

The up-front fixed fee in the subscription model is typically nonrefundable and independent of future consumption; thus, it can be regarded as a sunk cost (Dick & Lord, 1998; Zhang et al., 2021). Normative economic theories suggest that a sunk cost should not be taken into account when making subsequent consumption decisions. However, behavioral economic theories propose that individuals may exhibit the sunk cost fallacy (Arkes & Blumer, 1985; Iyengar et al., 2022; Thaler, 1980) such that they have an irrational escalation of commitment to amortize their psychological cost (Friedman et al., 2007). In a similar vein, evidence suggests that the up-front fixed fee can prompt a high tendency to consume more than rationally planned (Zhang et al., 2021). Notably, the existing literature fails to consider how the price adjustment of fixed fees strategy impacts future consumption through the sunk cost effect. While it is straightforward that the effect of an individual's pressure of past payments on future usage should increase with the size of this irrecoverable payment (Gourville & Soman, 1998; Thaler, 1985), the substantial heterogeneity among individuals in terms of their susceptibility to the sunk cost may present different responses to price adjustment (De Bruin et al., 2007, 2014).

With the subscription price of the fixed fee adjusted to a lower level, different consumer segments in the market should be considered, since individuals may have different sensitivity to firms' promotion strategies (Palazón & Delgado, 2009). More specifically, if the up-front fixed fee was initially high, only low price-conscious consumers would have been attracted to the subscription. These existing subscribers would not be willing to devote more time searching or waiting for a lower price (Lichtenstein et al., 1993), indicating that they have a higher time opportunity cost but are less susceptible to monetary cost. Further, it is well-known that the consumption of information goods is a time-consuming process (Dey et al., 2013; Hoang & Kauffman, 2018), which entails time opportunity cost. This is more prominent when consumers need to consume the information goods offline, due to the existence of extra travel costs on top of the time investment. In this regard, the existing low price-conscious subscribers would be less susceptible to the monetary sunk cost induced by up-front fixed fees. They would be less likely to irrationally invest more time and effort into consuming the information goods, even if the consumption does not require any additional cash outlay. After the fixed fee is adjusted to a lower level, we expect these existing consumers will probably not change their consumption levels.

On the other hand, equivalent price discounts may not be valued similarly by highly price-conscious consumers. Since these consumers process price information extensively, they are more conscious about the value of the promotion (Palazón & Delgado, 2009). Thus, the downward price adjustment of the fixed fee is likely to shift the composition of the user base (Diamond, 1971), attracting a significant number of subscribers who have high price consciousness. This segment of customers, cognitively engaged with price (Lichtenstein et al., 1993), likely has a relatively lower time opportunity cost and is hence more susceptible to the sunk cost fallacy (Roth et al., 2015). Following their up-front payment for the subscription service, these new subscribers are likely to increase their consumption to amortize both the psychological burden and the cost per unit.

It is worth noting that the anticipated increase in consumption is not merely a result of the typical discount effect associated with a pay-per-unit model. In a pay-per-unit model, the discount effect tends to encourage customers to consistently pay the discounted price in exchange for the product/service every time, with the effect remaining constant as long as the discount is applicable. In contrast, the subscription fee in our context is paid upfront and is unrelated to customers' future consumption, rendering it a sunk cost. Furthermore, the subscription business model separates the payment and consumption of a transaction, which can impact a person's likelihood of consuming the pending benefit (Gourville & Soman, 1998; Roth et al., 2015). In particular, people will gradually adapt to their upstream payment with the passage of time, thereby diminishing the sunk cost impact on further consumption decisions (Hafenbrack et al., 2014).

In summary, by considering these two segments of customers who react differently to the price adjustment strategy of the subscription service, we posit that although low price-conscious subscribers do not change their consumption patterns, highly price-conscious customers will be attracted to subscribe and increase their consumption due to a large sunk cost bias. As a result, we expect the observed increase in overall consumption. We propose the following hypothesis:

H1: In the fixed-fee regime of information goods, with the price adjusted to a lower level, there would be an increase in the overall consumption and the effect would recede over time.

As a typical experience good, the consumption of information goods involves risks, as the quality and fitness are quite uncertain prior to consumption (Erdem et al., 2006). Consumers generally rely on signals such as popularity (Tucker & Zhang, 2011; Zhang et al., 2020) and word-of-mouth (Chevalier & Mayzlin, 2006; Karniouchina, 2011; Liu, 2006) to cope with this risk and guide purchases (Akerlof, 1970; Shimp & Bearden, 1982). Generally, "hit" or high-popularity products represent a more familiar and low-risk choice, while niche or low-popularity products represent a higher-risk choice for the consumer (Bockstedt & Goh, 2014). In a market applying the pay-per-unit business model, customers will likely reduce risks by following other people's choices and choosing high-popularity goods. However, in a subscription market where the up-front fixed payment creates a sunk cost for customers, the risk propensity for consumption is probably different for several reasons.

First, the decision situation with payment as a sunk cost is framed as a choice involving sure losses (Ho & Zhang, 2008) such that forgoing subsequent consumption leads to an inferior result or even a total loss of the up-front payment. It is well documented in prospect theory that individuals tend to behave in a risk-seeking manner in loss situations (Kahneman & Tversky, 1979; Keil et al., 2000a; Tait & Miller, 2019; Thaler, 1980). As mentioned above, a downward price adjustment of the fixed fee will attract highly price-conscious consumers (who are more susceptible to the sunk cost fallacy) to the subscription service (Roth et al., 2015). Thus, the incurred sunk cost would then promote these new subscribers to be more risk-seeking. Second, prior studies have referred to risk-taking theory to explain how sunk costs affect decision makers' behaviors from another perspective (Keil et al., 2000b). Specifically, an inverse relationship exists between the level of sunk costs and risk perception. That is to say, higher levels of sunk costs should lower a decision maker's assessment of the risk inherent in a situation (Sitkin & Pablo, 1992), causing them to be more willing to take risky actions. Thus, new subscribers who are very sensitive to sunk costs would perceive niche information goods as less risky than before and be more willing to choose them. Third, the sunk costs in subscription services separate the payment from consumption (Schlereth & Skiera, 2012), which results in an increased temporal distance between the costs and benefits of a transaction, as compared to the traditional pay-per-unit model. As widely discussed in prior literature (Liberman et al., 2007), high temporal distance induces high-level construal and thus more abstract thinking (Trautmann & van de Kuilen, 2012). Decision makers tend to focus on the superordinate goal of obtaining desirable outcomes with some risks under high-level construal (Sagristano et al., 2002). In this regard, we expect that the increased temporal distance created by the up-front fixed fee will lead to new subscribers' high-level thinking that they are more likely to take some risks.

Therefore, we expect to observe a higher portion of sales of niche products as consumers exhibit a bias towards the sunk cost and increase their risk-seeking behaviors. This is also in line with the literature on the purchase quantity and balance heuristic (Cheng et al., 2012). As the purchase quantity increases, people tend to employ a balance heuristic to distribute their multiple choices among the available options to achieve a balanced state and satisfy their variety-seeking tendency (Cheng et al., 2012). Thus, with the hypothesized increase in overall consumption (i.e., H1), we expect that newly attracted consumers would spread their consumption among both hit and niche products, compared with the previous situation wherein they primarily focus on hit products. Our hypothesis is formulated as follows:

H2: In the fixed-fee regime of information goods, the effect of price adjustment on overall consumption is stronger for niche information goods.

4 Context and Data

4.1 A Quasi-Natural Experiment

As a typical subscription service for information goods, the prevalence of several subscription-based movie ticketing services is representative of answering our proposed research question. These digital services, such as MoviePass, AMC's A-List, and Cinemark's Movie Club, overturn the traditional model of per-movie ticket purchases and instead give subscribers access to a predetermined number of movies at one or more theaters for a certain period in exchange for paying a recurring fixed fee (typically monthly).

We focus on the start-up company MoviePass, which provides a subscription-based movie ticketing service that is only available in the United States. Operationalized through a geolocation-based smartphone app, the service allows a subscriber to attend a specific number of movies per month for a monthly fixed subscription fee. Since it was a third-party platform and did not require an affiliation with theaters or studios,[1] MoviePass was available in all theaters and had no influence on movie release schedules, show times, or other factors potentially endogenous with revenue. MoviePass paid movie theaters the full ticket price for each movie viewed by its subscribers, using the movie tickets as a loss leader in the hopes of monetizing user data. In this regard, the resulting movie consumption changes should be directly reflected in the aggregate movie box office revenue.

On August 15, 2017, in conjunction with its acquisition by Helios and Matheson,[2] MoviePass dramatically adjusted its pricing strategy, changing from several more expensive subscription tiers across multiple locations to a single consolidated model that provided up to one movie ticket per day for $9.95 per month (Buckley, 2018). The equivalent unlimited plan prior to August 15 cost $50 per month. The downward price adjustment helped MoviePass attract many subscribers in a short time period. Within six months, the number of subscribers increased to more than 2 million from less than 150,000 members before the price adjustment of the fixed fee. Hence, the price adjustment shock of MoviePass provided a unique opportunity for us to utilize a quasi-experimental design to quantify its impact on overall consumption, helping rule out the effects of confounding factors that also influence movie box office revenues.

Figure 1 provides evidence of the exogenous shock that occurred when MoviePass suddenly adjusted its fixed subscription fee in mid-August 2017. The Google trends search data demonstrate a significant increase in interest in the service starting exactly at the date of the price adjustment policy. This spike suggests that the sudden change in MoviePass's fixed fee was not anticipated by potential consumers.

[1] Each time users utilize the MoviePass mobile app to check in to a theater and choose a movie and showtime, the cost of the ticket is loaded to a prepaid debit card. Then users can use the MoviePass physical card to purchase tickets from theaters as usual. To the theater, it looks as if customers are paying with a normal credit card.

[2] Though launched in 2011, MoviePass was not well known and had been struggling to make a dent in the theater business as of mid-2017 (Statt, 2019). MoviePass was purchased by analytics firm Helios and Matheson in August 2017, with the goal of user data collection and monetization.

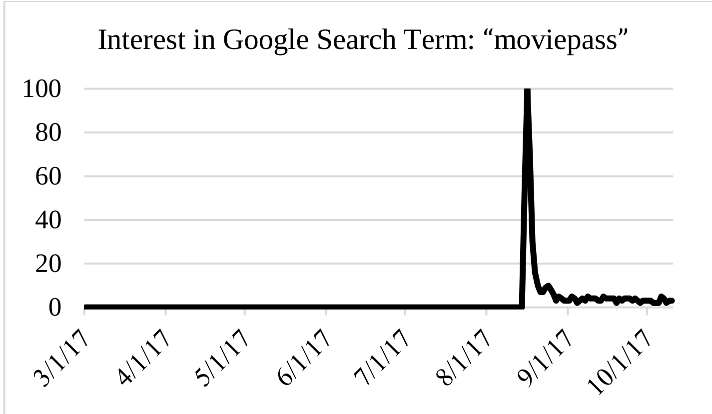


Figure 1. Google Trends Search Interest in the Term “MoviePass”

4.2 Dataset

We used movies’ box office revenue information as the measurement for overall consumption, which we collected from OpusData[3] for all movies released in the US and internationally from 2016 to 2018. We constructed a panel of movie revenues from February 2017 to February 2018,[4] six months before and after the event of the sudden price adjustment on MoviePass.

In addition to revenue, we included the movie’s name (identifier), observation date, release territory, whether the observation date was a holiday, the number of theaters showing the movie, and the number of days since the release of the movie. To prepare the data, we selected movies released in Australia as our control group since Australia had the most overlapping movies with the US in our observation period. Therefore, 200 matched movies and 3995 weekend observations were included in our panel dataset. Details of the matching procedure are discussed in the next section.

Following prior movie literature (Kulkarni et al., 2012), competition, advertising, and word-of-mouth are also important factors in predicting movie box office revenue. Thus, we further collected relevant data from three sources: Google Trends, Rotten Tomatoes, and IMDB. Since we were unable to obtain daily or weekly advertising data, weekly Google Trends data for each movie was used as a proxy variable for advertising information. Given that the goal of advertising is to increase potential moviegoers’ awareness of a movie, increased awareness may induce moviegoers to search for the movie. From this standpoint, the weekly advertising expenditure of a movie is positively associated with consumer search volume for the movie (Chen et al., 2015).

Rotten Tomatoes and IMDB are popular movie review platforms, and reviews from these two platforms also serve as good indicators of word-of-mouth. We captured the ratings and volume of reviews for each movie during our data periods from these two platforms and aggregated them at the weekly level. Competition was measured by the number of movies released in the same time period as a given movie, as well as the corresponding word-of-mouth information about these movies. Competition increases with the number of movies released in the same period, especially when contemporary movies have better reputations. Summary statistics of key variables are presented in Appendix A.

5 Empirical Strategies

5.1 Difference-in-Differences (DID) Model

To answer our research questions, we needed to compare the actual movie box office revenue (i.e., movie consumption) after the sudden price adjustment to some plausible counterfactual that would have occurred in the absence of the event. Though we were unable to observe the box office performance of the same movie in the same territory for both situations, we were able to observe the box office revenue of the same movies released at the same time in other countries, which were not affected by the intervention. As explained previously, movies released in Australia formed our control group since Australia had the most overlapping movies with the US in our observation period. Since the MoviePass subscription service was only available in the United States, Australia did not undergo the sudden price adjustment event. We matched movies released in both Australia and the US

[3] https://www.opusdata.com/documentation/index.php/Database_Extracts

[4] After February 2018, MoviePass implemented several small price tactics changes. So, we used a time window of February 2017 to February 2018 to avoid the influence of potential confounding factors. The subset ranging from February 2016 to February 2017 was used for robustness checks.

in the given observation period and included the matched movies in our sample. All US movies had corresponding *self-control* observations in Australia in the same time period. Movies that were released for less than 4 weeks in either territory were removed from our data analyses.[5]

We used a difference-in-differences (DID) model (Bertrand et al., 2004) to estimate the average treatment effect of the price adjustment policy. The DID model is a widely used approach to derive causal effects by comparing outcome differences before and after an exogenous shock for a treatment group to that of a control group. Our unit of analysis is at the movie-week level from February 2017 to February 2018, six months before and six months after the price adjustment policy in mid-August 2017. We then estimated a DID model to the matched sample to identify the causal effect of the fixed fee price adjustment on overall consumption. Our empirical model is specified as:

$$\begin{aligned} ln(Revenue_{ijt}) = a_0 &+ a_1(After_t \times MoviePass_j) \\ &+ a_2 After_t + a_3 MoviePass_j \\ &+ a_4 ln(Release_{ijt}) \\ &+ a_5 ln(Theaters_{ijt}) \\ &+ a_6 Holiday_{jt} \\ &+ a_7 Comp\_movie\_count_{ijt} \\ &+ a_8 Comp\_avg\_rating_{ijt} \\ &+ a_9 ln(Comp\_avg\_volume_{ijt}) \\ &+ a_{10} ln(Google\_trends_{ijt}) \\ &+ a_{11} ln(Pre\_volume_{it}) \\ &+ a_{12} Pre\_valence_{it} + \mu_i + \omega_t \\ &+ \varepsilon_{ijt} \end{aligned} \tag{1}$$

where *ln(Revenue$_{ijt}$)* is the log-transformed weekend movie box office revenue for movie *i* in country *j* at week *t*.[6] *After$_t$* equals 1 if time period *t* is after the date of the price adjustment policy, and 0 otherwise. *MoviePass$_j$* equals 1 if a movie was released in the treatment group (i.e., US), and 0 if it was released in the control group. Thus, the interaction term *After$_t$* × *MoviePass$_j$* equals 1 if a movie in the US was released in a time period after the date of price adjustment policy, and 0 otherwise. Our key variable of interest is the coefficient estimate a_1, which captures the average treatment effect of the price adjustment of the fixed fee on movies' overall consumption.

We also included several time-variant features as control variables. Table A1 in Appendix A gives the definition of each covariate. *Holiday$_{jt}$* is a dummy variable that indicates if week *t* falls on a national holiday in country *j* to control for the possible holiday effects. μ_i captures the movie fixed effects, such as time-invariant genre of movies; ω_t captures the week fixed effects, such as seasonality; and ε_{ijt} is the mean zero error term. Although we collected reviewers' rating information from both the IMDB and Rotten Tomatoes platforms to construct competition and word-of-mouth related variables, we used those from IMDB in our main analyses and those from Rotten Tomatoes in our robustness checks.

5.2 Relative Time Model

One of the most important assumptions of the DID approach is that the treatment and control groups share the same trend during the period prior to the treatment (Bertrand et al., 2004). In our context, this means that the movie box office revenues in both the US and Australian markets would have developed in the same way had the MoviePass price adjustment event not taken place. Parallel pre-treatment trends help support the claim that the differences in the trends between control and treated groups are indeed caused by the price adjustment of the subscription service. Thus, to test whether the parallel trends assumption is satisfied, we applied the relative time model (Peukert et al., 2017) with the inclusion of both the leads and lags in the periods. This model enabled us to determine whether a pre-treatment trend exists. *Week$_t$(k)* equals 1 if week *t* is *k* week(s) prior to the MoviePass price adjustment event and *Week$_t$(m)* equals 1 if week *t* is *m* week(s) after the event. Thus, the coefficient set θ_k captures the pre-treatment trend, while those of θ_m capture the effect of the event in each post-treatment period. If θ_k are insignificant, the parallel trends assumption is satisfied, suggesting that it is reasonable to use the DID method in our context. Specifically, the model can be written as:

$$\begin{aligned} ln(Revenue_{ijt}) = a_0 &+ \sum_k \big(\beta_k Week_t(k) \\ &+ \theta_k (Week_t(k) \times MoviePass_j)\big) \\ &+ \sum_m \big(\beta_m Week_t(m) \\ &+ \theta_m (Week_t(m) \\ &\times MoviePass_j)\big) \\ &+ a_1 MoviePass_j \\ &+ a_2 ln(Release_{ijt}) \\ &+ a_3 ln(Theaters_{ijt}) \\ &+ a_4 Holiday_{jt} \\ &+ a_5 Comp\_movie\_count_{ijt} \\ &+ a_6 Comp\_avg\_rating_{ijt} \\ &+ a_7 ln(Comp\_avg\_volume_{ijt}) \\ &+ a_8 ln(Google\_trends_{ijt}) \\ &+ a_9 ln(Pre\_volume_{it}) \\ &+ a_{10} Pre\_valence_{it} + \mu_i + \omega_t \\ &+ \varepsilon_{ijt} \end{aligned} \tag{2}$$

[5] Since most 3D movies also have 2D versions, we didn't exclude them in the following analyses. In fact, we found similar results with or without the 3D movie observations.

[6] We employed the logged outcome variable because it exhibited high skewness, and the percentage changes in movies' box office revenue provided a more meaningful representation than the absolute value changes.

Table 1. Main Results with Different Time Windows

Variables	2×3 months	2×4 months	2×5 months	2×6 months
$After_t \times MoviePass_j$	0.302***(0.077)	0.266***(0.066)	0.211***(0.057)	0.115* (0.048)
$After_t$	-0.830***(0.151)	-0.983***(0.161)	-1.049***(0.166)	-1.597***(0.166)
$MoviePass_j$	0.359***(0.100)	0.340***(0.093)	0.201**(0.077)	0.307***(0.059)
$ln(Release_{ijt})$	-0.666***(0.021)	-0.666***(0.018)	-0.652***(0.016)	-0.673***(0.014)
$ln(Theaters_{ijt})$	0.960***(0.013)	0.960***(0.011)	0.966***(0.010)	0.960***(0.009)
$Holiday_{jt}$	0.283 (0.157)	0.378*(0.149)	-0.042 (0.080)	0.106 (0.066)
$Comp\_movie\_count_{ijt}$	-0.009 (0.008)	-0.005 (0.007)	0.004 (0.005)	0.003 (0.004)
$Comp\_avg\_rating_{ijt}$	-0.417 (0.307)	-0.243 (0.276)	-0.569*(0.235)	-0.154 (0.196)
$ln(Comp\_avg\_volume_{ijt})$	0.109 (0.295)	-0.139 (0.199)	0.261 (0.166)	0.030 (0.141)
$ln(Google\_trends_{ijt})$	0.085***(0.017)	0.088***(0.014)	0.089***(0.014)	0.074***(0.012)
$ln(Pre\_volume_{it})$	0.050*(0.022)	0.059**(0.019)	0.066***(0.018)	0.081***(0.016)
$Pre\_valence_{it}$	0.028 (0.015)	0.023 (0.013)	0.014 (0.012)	0.010 (0.011)
Movie fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Num. obs.	2040	2646	3219	3995
Adjusted R-square	0.954	0.955	0.954	0.955
Note: ***p < 0.01; **p < 0.05; *p < 0.1. Robust standard errors are shown in parentheses.				

6 Empirical Results

6.1 Main Results

To examine whether the price adjustment of a fixed fee can produce short- or long-term effects, we conducted the analyses by using DID approaches on different time windows. We choose 3 months, 4 months, 5 months, and 6 months, both before and after the event, respectively.[7] The results from Table 1 are generally similar. The coefficients of the key interaction term $After_t \times MoviePass_j$ are all positively significant across four different study periods. The magnitude ranges from 0.115 to 0.302 and shows a decreasing trend as the time period expands. This suggests that the weekend revenues of an average movie increased between 12.19%[8] to 35.26% in the following six months after the downward price adjustment of the fixed subscription fee. This suggests that a great number of new customers were attracted to the subscription service (i.e., from less than 150,000 members to more than 2 billion). In Section 8, we present our post hoc experimental study, which showed that this new segment of customers was highly price conscious since they were willing to pay for the subscription service only if the fixed fee significantly dropped to a lower level. They had a relatively lower time opportunity cost and were more susceptible to the sunk cost fallacy, which was caused by the up-front payment. Thus, they increased their movie consumption to amortize the psychological burden as well as the cost per movie. Further, we observed that the marginal effect of price adjustment decreased in the long term (i.e., the coefficients drop from 0.302 to 0.115 in six months), which can be explained by the "payment depreciation" (Gourville & Soman, 1998). Since subscription services temporally separate consumers' transaction costs and benefits, people will gradually adapt to their upstream payment with the passage of time, thereby diminishing the sunk cost impact on further consumption decisions. Such a relationship between consumption levels and the recency of payment also suggests the presence of any sunk cost effect (Goli et al., 2022). Overall, these results support H1.

In terms of control variables, most of the findings are as expected. The coefficients of $ln(Release_{ijt})$ are statistically negative, indicating that box office revenue for a specific movie gradually decreased over time. Consistent with the findings in prior literature (e.g., Duan et al., 2008; Liu, 2006), the number of screens showing the movie (i.e., $ln(Theaters_{ijt})$) had a positive effect on box office revenue. The estimated coefficients of $ln(Google\_trends_{ijt})$ and $ln(Pre\_volume_{ijt})$ are also statistically positive, validating the importance of advertising and word-of-mouth information in predicting box office revenue.

[7] The following sections report further analyses that were conducted on the complete panel data ranging from February 2017 to February 2018 (i.e., a time window of 2 × 6 months).

[8] $(e^{0.115}$-1) ×100% =12.19%.

Table 2. Testing Parallel Pre-Treatment Trends

Variables	Coefficient (*SE*)	95% confidence interval
$Week_t$ (≤ -4) × $MoviePass_j$	0.004 (0.136)	[-0.262, 0.271]
$Week_t$ (-3) × $MoviePass_j$	0.046 (0.134)	[-0.218, 0.309]
$Week_t$ (-2) × $MoviePass_j$	-0.133 (0.137)	[-0.402, 0.135]
$Week_t$ (-1) × $MoviePass_j$	0.115 (0.145)	[-0.168, 0.399]
$Week_t$ (1) × $MoviePass_j$	0.461^{***}(0.130)	[0.207, 0.715]
$Week_t$ (2) × $MoviePass_j$	0.491^{***}(0.131)	[0.235, 0.747]
$Week_t$ (3) × $MoviePass_j$	0.505^{***}(0.129)	[0.252, 0.758]
$Week_t$ (≥4) × $MoviePass_j$	0.364^{***}(0.133)	[0.103, 0.626]
Movie fixed effects	Yes	
Week fixed effects	Yes	
Num. obs.	3995	
Adjusted *R*-square	0.934	

Note: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. Robust standard errors are shown in parentheses.

6.2 Parallel Pre-Treatment Trends

The results from the relative time model are shown in Table 2. All coefficients of treatment and week dummies in the pre-intervention periods are statistically insignificant, supporting common trends of box office revenue between the US and Australian markets before the event. This result provides further support for our identification strategy. The causal effect of the price adjustment of the fixed fee on the observed increases in box office revenue is unlikely to have been driven by a false trend starting prior to the policy change. Moreover, consistent with our main findings in Table 1, all coefficients of treatment and week dummies in the post-intervention periods are positive and significant, further supporting H1.

6.3 Heterogeneous Effects

Until now, we have focused on the main effect of the price adjustment of subscription services on overall consumption. However, we still do not know if certain types of information goods enjoy more benefits from such downward price adjustments. As consumers are attracted to certain content (Qiu et al., 2015), how consumers react to niche or hit information goods after the price adjustment of the fixed subscription fee is of interest. Based on H2, the downward price adjustment of the fixed fee should induce consumers' risk-seeking behavior. The newly attracted consumers would spread their consumption among both hit and niche products, compared to the previous situation where they primarily focused on hit products. Niche goods are defined as products that are less known to the general consumer population and appeal to a smaller group of people (Bockstedt & Goh, 2014), which is the opposite of highly popular hit products. Thus, we used low-popularity products to proxy niche products. We first examine whether there are heterogeneous effects between high-popularity and low-popularity goods, and then discuss the role of *quality* and *natural breadth of appeal*, which are the two potential reasons for popularity (Tucker & Zhang, 2011). In particular, if the downward price adjustment indeed attracts more consumption towards less popular but high-quality goods, it can expand the potential market of niche information goods to interested audiences.

6.3.1 Heterogeneous Effects by Popularity

Much research has shown that user ratings, i.e., online word-of-mouth, contain information about the popularity and average quality of information goods and have an effect on consumption (Chintagunta et al., 2010). We constructed popularity measures from Rotten Tomatoes and IMDB data, respectively, because they are popular movie review platforms internationally and have been widely used in prior studies (Adomavicius et al., 2013; Yu et al., 2022). Accordingly, we used the number of ratings given by regular audiences in Rotten Tomatoes (denoted as RT_count_i), and the number of ratings given by reviewers in IMDB (denoted as $IMDB\_count_i$) as popularity measurements. By using different measurements in our model, we can cross-validate whether the heterogeneous effect by popularity is robust to different popularity indicators.

To examine how popularity moderates the effect of downward price adjustment on consumption, we first included a three-way interaction term of $After_t \times MoviePass_j \times Popularity_i$, as shown in the following equation. We also included all lower-order interactive terms except $Popularity_i$, which is collinear with the movie fixed effects.

$$\begin{aligned} ln(Revenue_{ijt}) = a_0 &+ a_1(After_t \times MoviePass_j \\ &\times Popularity_i) \\ &+ a_2(After_t \times MoviePass_j) \\ &+ a_3(MoviePass_j \\ &\times Popularity_i) \\ &+ a_4(After_t \times Popularity_i) \\ &+ a_5 After_t + a_6 MoviePass_j \\ &+ a_7 ln(Release_{ijt}) \\ &+ a_8 ln(Theaters_{ijt}) \\ &+ a_9 Holiday_{jt} \\ &+ a_{10} Comp\_movie\_count_{ijt} \\ &+ a_{11} Comp\_avg\_rating_{ijt} \\ &+ a_{12} ln(Comp\_avg\_volume_{ijt}) \\ &+ a_{13} ln(Google\_trends_{ijt}) \\ &+ a_{14} ln(Pre\_volume_{it}) \\ &+ a_{15} Pre\_valence_{it} + \mu_i + \omega_t \\ &+ \varepsilon_{ijt} \end{aligned} \quad (3)$$

Second, we conducted a segment-level analysis (Wu et al., 2021) by dividing our dataset into two subsamples (i.e., the high-popularity movies versus low-popularity movies). Compared with the model that treats popularity as a moderator, this kind of segment-level analysis helped us determine not only whether the effect of price adjustment was greater for low-popularity goods over high-popularity ones but also the absolute magnitude of the effect for each segment (Rishika et al., 2013; Wu et al., 2021). We defined "high-popularity" movies as the top 70th percentile of RT_count_i (or $IMDB\_count_i$), and "low-popularity" movies as the bottom 30th percentile of the RT_count_i (or $IMDB\_count_i$). By using two different measurements of popularity (i.e., RT_count_i and $IMDB\_count_i$) and replicating our model estimation respectively, we were able to validate the robustness of our results. We then analyzed each segment to distinguish the effects of price adjustment of the fixed subscription fee at the segment level by using our Model (1).

Formal data analyses are shown in Table 3. The key interactive term of interest $After_t \times MoviePass_j \times Popularity_i$ in Columns 1 and 4 of Table 3 captures the incremental effect of movie popularity. The coefficients are negative and significant, suggesting that the downward price adjustment induced more consumption for low-popularity goods (i.e., niche goods) than high-popularity goods (i.e., hit goods), supporting H2.

Columns 2-3 and 5-6 in Table 3 summarize the estimation results of the segment-level analysis. Consistently, niche goods (i.e., low-popularity movies) benefitted from the downward price adjustment, demonstrated by the coefficients of $After_t \times MoviePass_j$ being significantly positive, whereas the price adjustment policy did not increase the consumption of high-popularity goods. It suggests that niche goods received more exposure due to the downward price adjustment of the fixed fee, while high-popularity did not receive further awareness, which further validates H2.

6.3.2 The Role of Quality and Natural Breadth of Appeal

As argued by Tucker and Zhang (2011), there are two drivers of popularity: quality and the natural breadth of appeal. An item may be popular either because its quality is perceived to be high or because it caters to a broader range of tastes. We further investigated the factor driving the positive treatment effect on low-popularity goods. Similar to the above analyses, we conducted another two segment-level analyses by further dividing the low-popularity subset into two subsamples, based on quality and the natural breadth of appeal, respectively. First, we used each movie's average rating from Rotten Tomatoes (i.e., $RT\_avg\_rating_i$)[9] as the quality measurement and estimated the effect of downward price adjustment on low-quality and high-quality movies.[10] Second, rating variance is generally treated as an indicator of the natural breadth of appeal (Sun, 2012); therefore, upon seeing a movie of high variance, people may infer that the movie is a niche movie, as some consumers give a "like" rating while others give a "dislike" rating. Thus, high rating variance suggests a narrow appeal while low rating variance corresponds to a broad appeal. We utilize this measurement (i.e., movie's rating variance from Rotten Tomatoes) to estimate the effect of downward price adjustment on narrow-appeal and broad-appeal goods. The results are shown in Table 4.

Clearly, we can see that the observed positive treatment effect of low-popularity movies in Table 3 is mostly attributed to movies of high quality and those of narrow appeal, as the corresponding coefficients in both Columns 2 and 3 of Table 4 are significant and positive. There are no significant signs regarding movies of either low quality or broad appeal. This is probably because, among low-popularity movies, narrow-appeal movies of high quality have much higher desirability in terms of both enjoyment and diversity than broad-appeal movies of low quality. Thus, we can gain more insights into the treatment effect on niche goods (i.e., H2), that is, the price adjustment of the fixed fee has a stronger impact on low-popularity goods' consumption only if the low popularity is driven by narrow appeal and high quality.

7 Robustness Checks

7.1 Analyses Using Alternative Control Groups

In our main analysis, we used Australia as the control group due to it having the most overlapping movies with the US. Although we took country-specific effects into consideration, some potential unobservable characteristics (e.g., cultural similarity) may have also affected the results. To validate our findings, we used other countries (i.e., New Zealand, the UK, and Russia) as the control group, and reestimated Model (1). The results shown in Table 5 are consistent with our main analyses, providing further support for the validity of our findings. It is worth noting that the UK had a nearly identical subscription service to MoviePass—Sinemia—before the treatment time, but there was no price adjustment policy for Sinemia during our observation period. Thus, using the UK as an alternative control group further eases the concern about comparability between the treated group and the control group.

[9] We also utilized rating information obtained from IMDB as an alternative indicator for *quality*. The results are quite consistent with those using Rotten Tomatoes rating information.

[10] Similar to the above analysis, we defined "high-quality" movies as the top 70th percentile of $RT\_avg\_rating_i$ and "low-quality" movies as the bottom 30th percentile of the $RT\_avg\_rating_i$.

Table 3. The Moderating Effect of Popularity with Different Measurements

	Popularity indicator: RT_count_i			Popularity indicator: $IMDB\_count_i$		
Variables	(1) Continuous variable	(2) Low popularity	(3) High popularity	(4) Continuous variable	(5) Low popularity	(6) High popularity
$After_t \times MoviePass_j \times Popularity_i$	-0.060* (0.028)			-0.066* (0.026)		
$After_t \times MoviePass_j$	0.726** (0.278)	0.265** (0.090)	-0.051 (0.058)	0.854** (0.286)	0.251** (0.095)	-0.025 (0.061)
$MoviePass_j \times Popularity_i$	0.095*** (0.022)			0.080*** (0.019)		
$After_t \times Popularity_i$	-0.035 (0.029)			0.005 (0.027)		
$After_t$	-1.426*** (0.301)	-1.276*** (0.292)	-1.420*** (0.243)	-1.791*** (0.325)	-1.146** (0.350)	-1.818*** (0.240)
$MoviePass_j$	-0.606** (0.223)	0.108 (0.108)	0.345*** (0.077)	-0.564* (0.220)	0.120 (0.117)	0.552*** (0.079)
$ln(Release_{ijt})$	-0.668*** (0.014)	-0.653*** (0.022)	-0.665*** (0.024)	-0.667*** (0.014)	-0.649*** (0.023)	-0.747*** (0.023)
$ln(Theaters_{ijt})$	0.944*** (0.010)	0.932*** (0.016)	1.032*** (0.015)	0.949*** (0.010)	0.970*** (0.017)	0.968*** (0.015)
$Holiday_{jt}$	0.107 (0.066)	0.164 (0.119)	0.117 (0.091)	0.101 (0.066)	0.261 (0.144)	-0.028 (0.081)
$Comp\_movie\_count_{ijt}$	0.003 (0.004)	0.013 (0.007)	-0.002 (0.005)	0.004 (0.004)	0.009 (0.008)	-0.013* (0.005)
$Comp\_avg\_rating_{ijt}$	-0.182 (0.195)	0.080 (0.363)	-0.206 (0.246)	-0.221 (0.196)	-0.143 (0.389)	0.011 (0.249)
$ln(Comp\_avg\_volume_{ijt})$	0.040 (0.141)	-0.126 (0.268)	-0.007 (0.183)	0.062 (0.141)	0.160 (0.284)	-0.183 (0.185)
$ln(Google\_trends_{ijt})$	0.089*** (0.013)	0.072*** (0.016)	0.124*** (0.031)	0.084*** (0.013)	0.055*** (0.017)	0.047 (0.030)
$ln(Pre\_volume_{it})$	0.078*** (0.016)	0.076* (0.033)	0.046* (0.023)	0.080*** (0.016)	0.089* (0.035)	0.075** (0.023)
$Pre\_valence_{it}$	0.014 (0.011)	0.021 (0.015)	0.040 (0.033)	0.013 (0.011)	0.010 (0.016)	0.039 (0.038)
Movie fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	3995	1550	1689	3995	1345	1606
Adjusted R-square	0.955	0.915	0.968	0.955	0.917	0.969

Note: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. Robust standard errors are shown in parentheses.

Table 4. Segment-Level Analyses for Low-Popularity Information Goods

Variables	(1) Low quality	(2) High quality	(3) Narrow appeal	(4) Broad appeal
$After_t \times MoviePass_j$	0.283 (0.156)	0.532** (0.171)	0.379* (0.168)	0.247 (0.188)
$After_t$	-0.446 (0.705)	-2.288*** (0.511)	-1.519** (0.520)	-1.565* (0.613)
$MoviePass_j$	0.208 (0.193)	0.121 (0.192)	0.039 (0.194)	0.356 (0.218)
$ln(Release_{ijt})$	-0.670*** (0.045)	-0.589*** (0.043)	-0.628*** (0.039)	-0.652*** (0.050)
$ln(Theaters_{ijt})$	0.932*** (0.032)	0.950*** (0.032)	0.948*** (0.030)	0.957*** (0.037)
$Holiday_{jt}$	0.231 (0.237)	0.064 (0.196)	0.598** (0.216)	0.226 (0.240)
$Comp\_movie\_count_{ijt}$	0.008 (0.014)	0.010 (0.013)	0.023 (0.013)	-0.001 (0.014)
$Comp\_avg\_rating_{ijt}$	1.009 (0.660)	-0.957 (0.673)	1.066 (0.656)	-0.378 (0.746)

ln(Comp_avg_volume$_{ijt}$)	-0.962 (0.497)	0.721 (0.481)	-1.108* (0.471)	0.193 (0.555)
ln(Google_trends$_{ijt}$)	0.087** (0.032)	0.019 (0.027)	0.101** (0.032)	0.030 (0.029)
ln(Pre_volume$_{it}$)	0.061 (0.057)	0.120 (0.071)	0.035 (0.057)	0.050 (0.086)
Pre_valence$_{it}$	0.011 (0.035)	-0.007 (0.027)	0.004 (0.030)	0.003 (0.032)
Movie fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Num. obs.	522	479	537	459
Adjusted *R*-square	0.912	0.913	0.923	0.877
Note: ****p* < 0.01; ***p* < 0.05; **p* < 0.1. Robust standard errors are shown in parentheses.				

Table 5. Results of DID Model Using Alternative Controls

Variables	**Control group: New Zealand**	**Control group: United Kingdom**	**Control group: Russia**
After$_t$ × MoviePass$_j$	0.216**(0.081)	0.174*(0.080)	0.210*(0.104)
After$_t$	-1.978***(0.185)	-1.532***(0.253)	-1.385***(0.351)
MoviePass$_j$	1.503***(0.086)	0.689***(0.088)	1.349***(0.153)
ln(Release$_{ijt}$)	-0.780***(0.017)	-0.733***(0.032)	-0.731***(0.036)
ln(Theaters$_{ijt}$)	0.977***(0.011)	0.886***(0.019)	0.856***(0.019)
Holiday$_{jt}$	-0.020 (0.048)	0.140*(0.061)	0.037 (0.082)
Comp_movie_count$_{ijt}$	-0.019***(0.005)	-0.006 (0.011)	-0.006 (0.019)
Comp_avg_rating$_{ijt}$	1.193***(0.258)	0.873 (0.465)	0.230 (0.316)
ln(Comp_avg_volume$_{ijt}$)	-0.248 (0.197)	-0.562*(0.268)	-0.004 (0.244)
ln(Google_trends$_{ijt}$)	0.102***(0.013)	0.061*(0.028)	0.154***(0.030)
ln(Pre_volume$_{it}$)	0.051***(0.015)	0.125***(0.032)	-0.030 (0.035)
Pre_valence$_{it}$	-0.004 (0.016)	-0.050*(0.024)	-0.010 (0.051)
Movie fixed effects	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes
Num. obs.	2745	1219	754
Adjusted *R*-square	0.965	0.963	0.963
Note: ****p* < 0.01; ***p* < 0.05; **p* < 0.1. Robust standard errors are shown in parentheses.			

Furthermore, we utilized a synthetic control method to further alleviate the concern of comparability of the treated and control groups. This method involved, for each affected movie, the construction of a weighted combination of movies in the unaffected group to form a "synthetic control" movie that could best mirror the affected one (Krijestorac et al., 2020; Lu et al., 2021). It helped balance the effect of potential time-varying confounders between the treated and control groups. Since we had multiple treatment units (i.e., movies), we adopted a variant of the traditional synthetic control method—that is, a generalized synthetic control (GSC) method developed in Xu (2017). This method allows for multiple treated units and estimates the average treatment effects on these treated units based on an interactive fixed effects model.

All movies with life spans covering both before and after the treatment periods were used. Among them, movies released in the US served as our treated units, while those released in all countries except the US formed the set of potential control units, involving 86 countries after filtering movies with a total running time of less than 4 weeks. We present the findings of MoviePass's sudden price adjustment impact on movie box office revenues from the GSC method in Figure 2 and Figure 3. Figure 2 depicts the trajectory of movie box office revenue (log transformed) in the treatment group (i.e., the US) and its synthetic counterpart before and after the exogenous shock. First, the figure clearly shows that the synthetic control group matches the treatment group well during the pre-treatment period. After the fixed subscription fee drops to a significantly lower level, the box office revenue in the synthetic control group is always below the revenue in the treatment group, which suggests an increase in box office revenue in the US. Then, we calculated the treatment effect as the average gap (i.e., the average treatment effect on the treated, ATT) between the actual box office revenue in the US and the predicted box office revenues in the synthetic control during the post-treatment period. The results are illustrated in Figure 3, where the *x*-axis is the relative time (i.e., in weeks) to the price adjustment event and the *y*-axis is the estimated coefficient, which represents the gap between the affected and unaffected movies. The grey area represents the 95% confidence interval. We can see that the gap between treated units and synthetic control units is close to zero before the treatment and significantly higher than zero after the treatment, which reaffirms that MoviePass's price adjustment event led to an increase in box office revenues in the treated group.

7.2 Potential Confounders

Several MoviePass competitors entered the US movie ticket subscription market not long after MoviePass achieved huge success in attracting a great number of new members—including Sinemia and AMC Stubs A-List. But none of these competitors applied an aggressive price adjustment policy comparable to that of MoviePass, which attracted a great number of new subscribers in a short period of time and thus served as an important demand driver in the movie exhibition market.

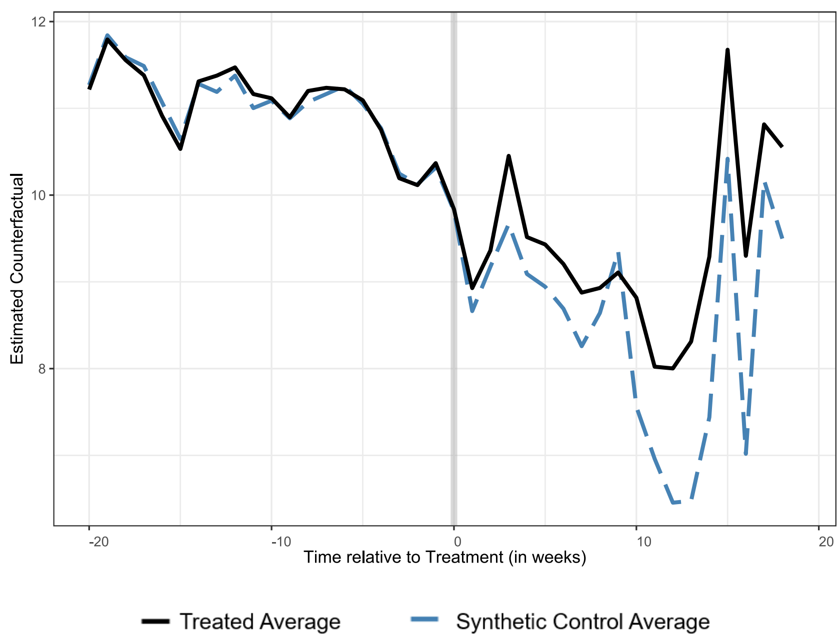


Figure 2. Trends of Box Office Revenue: Movies in the US vs. Movies in the Synthetic Control Group

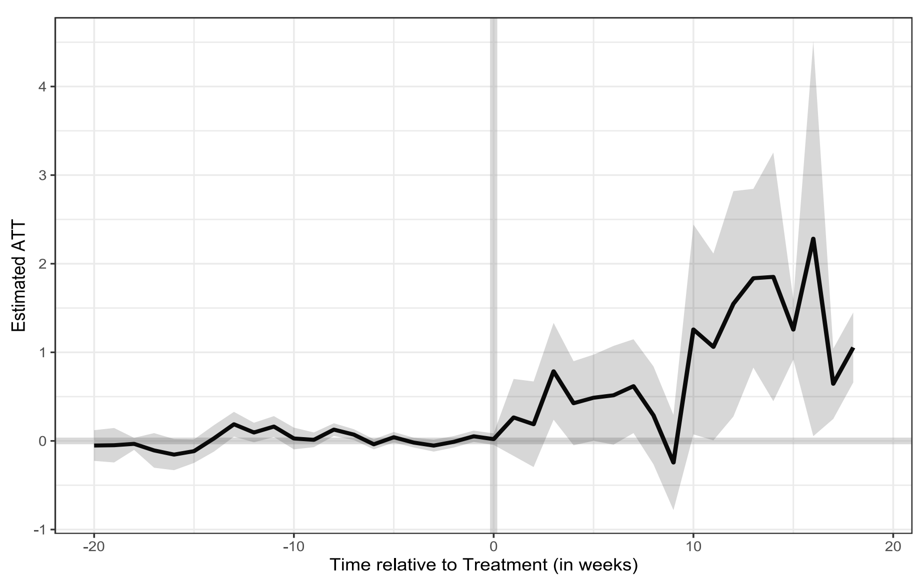


Figure 3. Gaps of Box Office Revenue Between the Treatment Group and the Synthetic Control Group

To avoid any confounding effects caused by the availability of other competitors, we narrowed the post-treatment window to the period between August 15, 2017, and November 30, 2017, during which other competing services were not available (i.e., MoviePass was the dominating subscription service). We henceforth focused on a short-term rather than long-term treatment effect. This selection provided the longest time window during which there was no significant confounding factor from other competing subscription services. The results are shown in Table 6 and they are quite consistent with our main findings.

More generally, the occurrence of some unobserved confounders during the same period as the price adjustment event may have contaminated the results. To eliminate this concern, we ran a counterfactual analysis by using Australia as the "placebo treatment group" and New Zealand as the control group (chosen based on maximum overlap among movies).[11] Insignificant results would help to rule out the possibility that the observed changes of movie box office revenues were due to some unknown shock. The estimation results are reported in Table 7; they are insignificant across the different time windows. These results provide evidence that the estimated treatment effects in our main analysis were less likely to be driven by other unobserved factors during the same period.

We conducted another robustness check to address the above concern by considering a pre-intervention time window (i.e., from February 2016 to February 2017). We artificially assigned a "placebo treatment" on August 15, 2016 (i.e., one year before the actual event), to see whether there was any increase in box office revenue due to this artificial treatment impacting our data. If the effects of these false treatment assignments were to be insignificant, it would confirm that it was the actual price adjustment event that led to changes in box office revenues. Coefficient estimates were statistically insignificant across different conditions (shown in Table 8), providing further evidence that the treatment effect in our main analysis was not due to unobserved confounders between February 2017 and February 2018. This placebo treatment test using pre-adjustment data also serves as evidence for the parallel pre-treatment trends across both groups (Aguiar et al., 2018; Datta et al., 2018).

7.3 Monthly Analyses

Up to this point, our analyses were conducted at the weekly level. In this robustness check, we investigated whether the results held when time granularity was extended from a week to a month. We reestimated our full model using a monthly panel dataset and report the results in Table 9. Despite some minor differences in magnitude, the new estimates remain qualitatively the same, suggesting that our results are robust even under a longer observation window.

Table 6. DID Results of Panel Data Ranging from February 2017 to November 2017

DV: $ln(Revenue_{ijt})$	
Variables	**Coefficient (*SE*)**
$After_t \times MoviePass_j$	0.194^{***}(0.049)
$After_t$	-1.454^{***}(0.164)
$MoviePass_j$	0.417^{***}(0.065)
$ln(Release_{ijt})$	-0.669^{***}(0.014)
$ln(Theaters_{ijt})$	0.964^{***}(0.010)
$Holiday_{jt}$	0.391^{***} (0.106)
$Comp\_movie\_count_{ijt}$	-0.006 (0.005)
$Comp\_avg\_rating_{ijt}$	0.197 (0.214)
$ln(Comp\_avg\_volume_{ijt})$	-0340^{*} (0.157)
$ln(Google\_trends_{ijt})$	0.084^{***} (0.013)
$ln(Pre\_volume_{it})$	0.063^{***}(0.016)
$Pre\_valence_{it}$	0.015 (0.011)
Movie fixed effects	Yes
Week fixed effects	Yes
Num. obs.	3350
Adjusted *R*-square	0.958
Note: $***p < 0.01$; $**p < 0.05$; $*p < 0.1$. Robust standard errors are shown in parentheses.	

[11] We also used matched movies in Australia and the UK as the treated group and control group, respectively. Although we had fewer matched samples, we reached consistent conclusions.

Table 7. Placebo Test 1: Counterfactual Treated Group

Variables	2×3 months	2×4 months	2×5 months	2×6 months
$After_t \times MoviePass_j$	0.062 (0.150)	0.117 (0.117)	0.029 (0.099)	0.035 (0.065)
$After_t$	-0.834***(0.214)	-0.819**(0.253)	-0.105 (0.272)	-0.233 (0.252)
$MoviePass_j$	0.427***(0.153)	0.592***(0.118)	0.691***(0.102)	0.713***(0.056)
$ln(Release_{ijt})$	-0.499***(0.027)	-0.549***(0.023)	-0.545***(0.021)	-0.575*** (0.018)
$ln(Theaters_{ijt})$	1.142***(0.020)	1.112***(0.017)	1.117***(0.016)	1.109*** (0.014)
$Holiday_{jt}$	0.138 (0.116)	0.090 (0.114)	0.081 (0.116)	-0.086 (0.081)
$Comp\_movie\_count_{ijt}$	0.032*(0.013)	0.009 (0.011)	0.003 (0.010)	0.004 (0.006)
$Comp\_avg\_rating_{ijt}$	-0.412 (0.369)	-0.149 (0.232)	-0.229 (0.210)	-0.265 (0.192)
$ln(Comp\_avg\_volume_{ijt})$	-0.097 (0.202)	-0.318 (0.178)	-0.333 (0.170)	-0.330*(0.161)
$ln(Google\_trends_{ijt})$	0.086***(0.016)	0.074***(0.013)	0.072***(0.013)	0.064***(0.011)
$ln(Pre\_volume_{it})$	0.152***(0.029)	0.173***(0.025)	0.185***(0.023)	0.204***(0.021)
$Pre\_valence_{it}$	0.035*(0.017)	0.018 (0.015)	0.011 (0.014)	0.002 (0.013)
Movie fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Num. obs.	1556	2069	2489	3147
Adjusted R-square	0.935	0.936	0.935	0.934
Note: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. Robust standard errors are shown in parentheses.				

Table 8. Placebo Test 2: Counterfactual Event Occurrence

Variables	2×3 months	2×4 months	2×5 months	2×6 months
$After_t \times MoviePass_j$	-0.061 (0.057)	-0.061 (0.055)	0.027 (0.051)	-0.061 (0.047)
$After_t$	-0.524***(0.152)	-0.709***(0.157)	-0.653***(0.166)	-1.040*** (0.177)
$MoviePass_j$	0.497***(0.091)	0.549***(0.078)	0.379***(0.059)	0.408***(0.050)
$ln(Release_{ijt})$	-0.633***(0.020)	-0.648***(0.018)	-0.651***(0.016)	-0.614***(0.014)
$ln(Theaters_{ijt})$	0.987***(0.014)	0.992***(0.012)	0.979***(0.011)	0.998***(0.010)
$Holiday_{jt}$	0.023 (0.034)	-0.212 (0.171)	0.054 (0.080)	-0.082 (0.067)
$Comp\_movie\_count_{ijt}$	-0.017**(0.005)	-0.020***(0.005)	-0.012**(0.004)	-0.009**(0.003)
$Comp\_avg\_rating_{ijt}$	-0.762 (0.562)	-0.102 (0.483)	-0.380 (0.379)	0.654*(0.309)
$ln(Comp\_avg\_volume_{ijt})$	-0.401 (0.297)	-0.336 (0.246)	0.037 (0.186)	-0.435**(0.141)
$ln(Google\_trends_{ijt})$	0.019 (0.016)	0.013 (0.014)	0.025 (0.013)	0.049***(0.012)
$ln(Pre\_volume_{it})$	0.120***(0.021)	0.133***(0.019)	0.132***(0.017)	0.113***(0.016)
$Pre\_valence_{it}$	0.014 (0.016)	0.010 (0.014)	0.000 (0.013)	-0.001 (0.013)
Movie fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Num. obs.	2117	2756	3390	4287
Adjusted R-square	0.960	0.956	0.957	0.953
Note: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. Robust standard errors are shown in parentheses.				

Table 9. Robustness Check: Monthly Analyses

Variables	2×3 months	2×4 months	2×5 months	2×6 months
$After_t \times MoviePass_j$	0.316*(0.153)	0.310*(0.126)	0.303**(0.113)	0.206* (0.097)
$After_t$	-0.527**(0.203)	-0.736***(0.191)	-0.279 (0.165)	-0.223 (0.159)
$MoviePass_j$	0.657***(0.196)	0.633***(0.178)	-0.070 (0.152)	0.070 (0.127)
$ln(Release_{ijt})$	-0.680***(0.043)	-0.672***(0.035)	-0.609***(0.034)	-0.638***(0.029)
$ln(Theaters_{ijt})$	0.984***(0.026)	1.004***(0.022)	1.051***(0.021)	1.032***(0.019)
$Holiday_{jt}$	0.329 (0.191)	0.338*(0.162)	-0.065 (0.057)	0.010 (0.047)
$Comp\_movie\_count_{ijt}$	-0.044*(0.019)	-0.044*(0.016)	0.008 (0.010)	0.006 (0.008)
$Comp\_avg\_rating_{ijt}$	1.107 (0.597)	0.855 (0.506)	-0.873 (0.495)	-0.264 (0.428)
$ln(Comp\_avg\_volume_{ijt})$	-0.907 (0.560)	-1.011*(0.392)	0.371 (0.347)	0.065 (0.301)
$ln(Google\_trends_{ijt})$	0.125***(0.031)	0.146***(0.027)	0.120***(0.027)	0.112***(0.024)
$ln(Pre\_volume_{it})$	0.127**(0.044)	0.107**(0.037)	0.115**(0.036)	0.134***(0.032)
$Pre\_valence_{it}$	0.019 (0.041)	0.038 (0.035)	0.054 (0.034)	0.041 (0.031)
Movie fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Num. obs.	541	735	930	1159
Adjusted R-square	0.969	0.968	0.961	0.962
Note: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. Robust standard errors are shown in parentheses.				

8 Post Hoc Experimental Study

8.1 Design and Participants

Thus far, the empirical analyses have shown that movie consumption levels recede over time—users exhibit different movie consumption behaviors based on the recency of their subscription fee payment, suggesting an influence of the sunk cost effect. To further verify our proposed mechanism in a more straightforward manner, we constructed a hypothetical movie subscription scenario and implemented a randomized experiment on Amazon's Mechanical Turk (MTurk). Most importantly, we measured participants' price consciousness and their susceptibility to the sunk cost fallacy, which serve as key factors to validate our mechanism.

The experiment is designed as between-subjects, consisting of two treatment conditions: (1) a subscription service with the original, high up-front fee (denoted as high-price group) and (2) a subscription service with a low up-front fee after price adjustment (denoted as low-price group). We recruited 140 participants from MTurk, paying each participant 1 USD as compensation. After removing participants who failed attention and manipulation check questions or failed to complete the experiment, 126 valid observations remained. Among these, 63 participants were from the low-price group and 63 were from the high-price group.

8.2 Stimuli and Procedures

Experiment participants were first asked to reveal their movie-watching habits. A set of questions was presented, capturing their tendency, frequency, budget related to watching movies in theaters, and general preferences for niche or popular movies. All these measurements served as control variables for further data analyses.

After this pre-experiment survey, we then measured participants' price consciousness (adapted from Lichtenstein et al., 1993) and their resistance to sunk costs (adapted from De Bruin et al., 2007), respectively. All of these were used to uncover whether our proposed sunk cost mechanism underpins our findings. The resistance to sunk costs was evaluated using the adult decision-making competence (A-DMC) framework, which presented several questions with each involving a choice between two options. Participants were asked to rate their choices ranging from 1 (most likely to choose the sunk cost option) to 7 (most likely to choose the normatively correct option). Responses were averaged across these items and reverse-coded to indicate participants' susceptibility to the sunk cost fallacy. These questions and measurements were positioned ahead of the primary task to mitigate any potential influence of the manipulated movie subscription service on participants' responses.

Subsequently, participants were put in the scenario of making a subscription decision for a hypothetical subscription-based movie ticketing service. They were randomly assigned to one of the two treatment groups, with the *price of subscription fee* being manipulated. For consistency with MoviePass practices, we set the up-front fixed fees at $49.95[12] (i.e., high-price group) and $9.95 (i.e., low-price group) per month, respectively. In the low-price group, participants were told that the subscription fixed fee was adjusted downward from $49.95 to $9.95, which is consistent with MoviePass. The benefits (e.g., watching up to 30 movies per month) and restrictions (e.g., exclusion of 3D or IMAX movies) for subscribing to this service were kept the same as MoviePass. To eliminate potential brand bias, the subscription service was given the fake name "MovieGo." The "Next Page" button on the scenario description page appeared only after 15 seconds had elapsed, preventing participants from moving ahead too quickly without carefully reading the information. See Appendix B for the screenshot of the scenario description. Then, participants were asked to reveal their subscription intention to the described service using a 7-point Likert scale.

Upon making the subscription decision, participants were directed to a page focusing on measuring dependent variables related to their movie-watching preferences. They received the following instructions: "Given the decision you made (i.e., whether to subscribe to the service or not), please answer the following questions related to your movie-watching behavior." Specifically, each participant was required to answer questions on their movie consumption level, risk-taking intention when selecting movies, and preferences for niche movies. First, two questions were asked to elicit participants' movie consumption levels:[13] (1) "On the first weekend after you have made the subscription decision, how likely would you go to the cinema to watch a movie?" (referred to as *consumption intention*) and (2) "How many movies do you intend to watch during the first month of making the subscription decision?" (referred to as *consumption numbers*). Second, participants were asked about their risk-taking intentions when selecting movies to watch in theaters using a 7-point Likert scale.[14] Third, to measure their

[12] Before its price adjustment policy, the equivalent unlimited plan for MoviePass cost $50. In the experiment, we slightly modified it to $49.95 to eliminate any potential effects caused by round or precise numbers.

[13] Participants were informed that there would be sufficient new movie releases that also matched their preferences.

[14] Although most prior studies elicit users' naturalistic risk taking, such as the likelihood to engage in risk activities

preferences for niche movies, participants rated the extent to which they agreed with the statement "I prefer to stick to my own taste, and choose niche movies" on a 7-point Likert scale.

Finally, participants answered manipulation check questions and completed a short survey containing demographic questions (i.e., age, gender, education level, and familiarity with subscription-based movie ticketing services), serving as control variables in our analyses. A flow graph for the overall experimental procedures is presented in Appendix B.

8.3 Results Analyses

8.3.1 Manipulation and Randomization Checks

We first conducted the manipulation check by comparing the participants' perceived price level of the subscription fees across groups. The results showed that the participants in the low-price group (Mean = 3.73) perceived the fixed subscription fee as significantly lower than those in the high-price group (Mean = 5.54, $F(1,124) = 43.79$, $p < 0.001$), supporting the effectiveness of our price manipulation. For the randomization check, the *t*-test results (Table 10) show that there was no significant difference between participants in the two conditions with respect to their demographic information (e.g., age, gender, and education level) and movie habits (e.g., tendency, frequency, and budget related to watching movies in theaters). This confirms that there was no selection bias and that participants were randomly assigned to treatment groups.[15]

8.3.2 Descriptive Statistics

Before delving into the mechanism, we present some descriptive statistics of the experiment to replicate what we observed from our observational data. Specifically, we expected to see: (1) the downward price adjustment of up-front fixed fee inducing an increase in subscription intention, and (2) in each treatment group, the subscribers, as opposed to nonsubscribers, exhibiting higher movie consumption levels. Additionally, we expected that subscribers would take more risks when selecting movies and show a higher preference for niche movies.

For the above purposes, we first calculated the average subscription intention in the two treatment groups, which clearly shows that participants in the low-price group had a significantly higher subscription intention (Mean = 5.13) than those in the high-price group (Mean = 3.35, $F(1,124) = 23.59$, $p < 0.001$). Then we generated a binary variable, *subscription decision*, coded as 1 when participants' subscription intention scores exceeded 4 and as 0 otherwise. Using this criterion, 49 out of 63 participants in the low-price group opted to subscribe, in contrast to only 23 out of 63 participants in the high-price group.

We next compared the responses of subscribers and nonsubscribers in each treatment group. Figure 4reports the mean values of movie consumption intention and consumption numbers, aligning with our initial expectations. As there were more subscribers in the low-price condition, there is a difference in overall consumption levels between the two groups (consumption intention: $M_{low\text{-}price} = 5.75$, $M_{high\text{-}price} = 4.65$, $F(1,124) = 15.300$, $p < 0.001$; consumption numbers: $M_{low\text{-}price} = 6.16$, $M_{high\text{-}price} = 4.83$, $F(1,124) = 3.036$, $p < 0.1$). This observation is consistent with our earlier finding that the downward price adjustment of MoviePass leads to a significant increase in overall movie box office revenue (i.e., higher movie consumption).

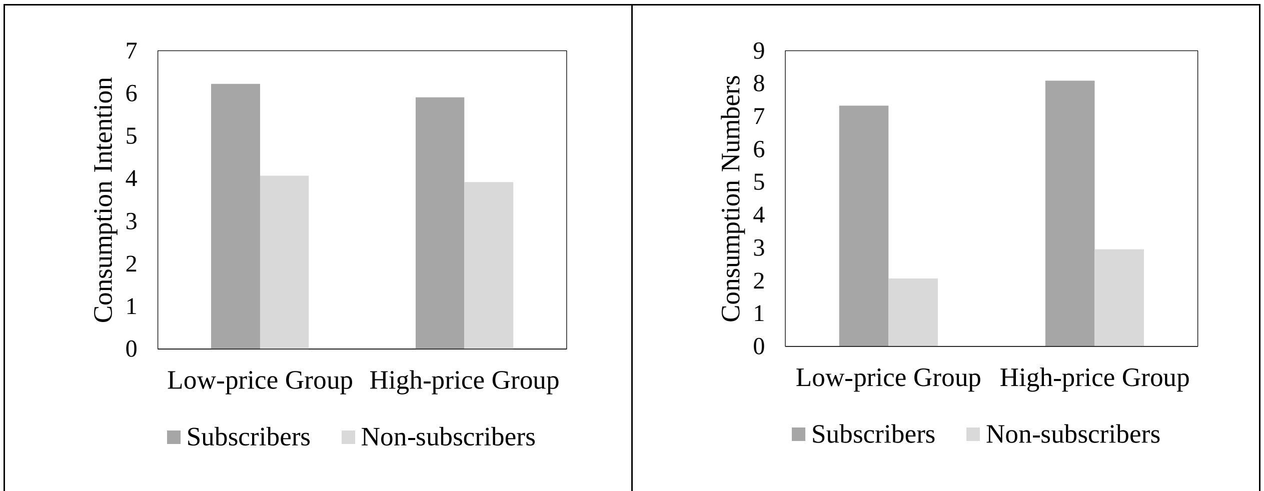
Figure 5 presents the mean values of risk-taking intention and niche movie preferences, respectively. Similarly, we can see that regardless of the treatment conditions, the subscribers exhibited a higher risk-taking intention for selecting movies in theaters, as well as a higher preference for niche movies. Again, this aligns with our earlier finding that the effect of price adjustment on overall consumption is stronger for niche goods.

Table 10. Randomization Checks of Covariates

	Age	Gender	Education level	Familiarity with subscription	Tendency	Frequency	Budget
Low-price Group	41.286 (12.703)	0.397 (0.493)	2.222 (0.991)	4.385 (1.503)	5.778 (1.202)	2.635 (1.339)	3.048 (1.672)
High-price Group	40.317 (10.719)	0.381 (0.490)	2.206 (0.765)	4.210 (1.547)	5.683 (1.121)	2.810 (1.424)	3.365 (1.743)
***p*-value**	0.644	0.856	0.920	0.337	0.645	0.479	0.299

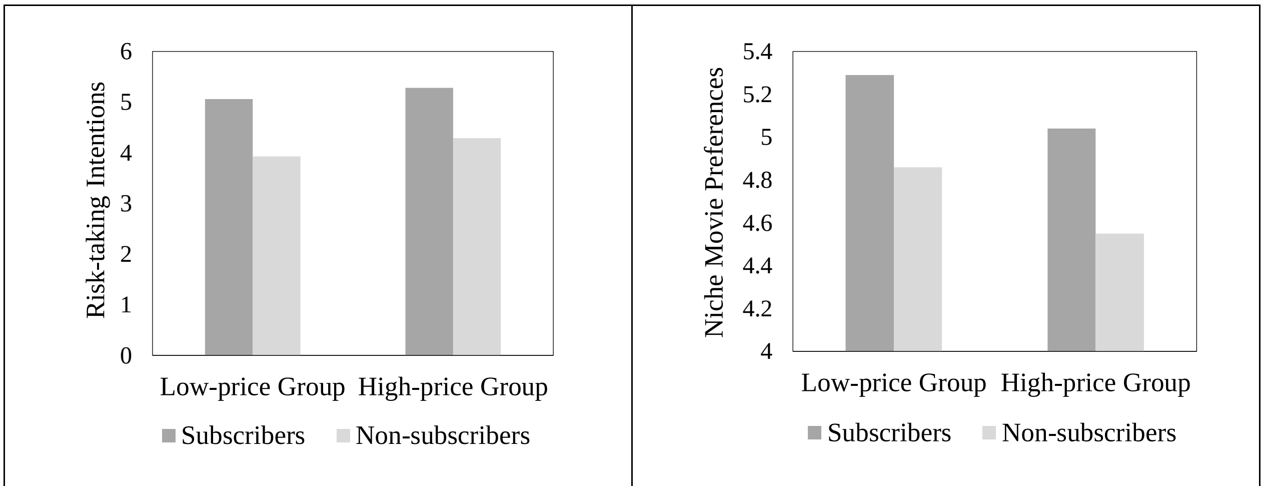
across different domains (Weber et al., 2002; Zhang et al., 2019), these measurements are not applicable to our scenario since they are not task-related.

[15] Despite this, we still considered them as covariates to conduct the data analyses.



(a) Consumption intention **(b) Consumption numbers**

Figure 4. Mean Values of Consumption Levels for Subscribers and Nonsubscribers



(a) Risk-taking intention **(b) Niche movie preferences**

Figure 5. Mean Values of Risk-Taking Intention and Niche Movie Preferences

8.3.3 Testing the Mechanism

We tested the underlying mechanism by examining two factors: price consciousness and sunk cost fallacy. Specifically, as the price of the fixed fee drops to a lower level, the subscription service begins to attract a different segment of customers who are highly price-conscious and are thus more susceptible to the sunk cost fallacy, leading to an increase in consumption levels and a higher preference for niche goods.

Subscription intention: We first categorized the participants into two natural groups based on their responses to the measurements of price consciousness (Cronbach's $\alpha = 0.883$). Participants with responses above the mean value were labeled as "high price consciousness," and as "low price consciousness" otherwise. Figure 6 suggests an interaction effect between price consciousness and the price level of the fixed fee on subscription intention. Specifically, as shown by the dotted line, the up-front subscription fee did not affect the low price-conscious participants' intention to subscribe to the service ($M_{low\text{-}price} = 4.42$, $M_{high\text{-}price} = 3.71$, $F(1,48) = 1.408$, $p = 0.241$), while the high price-conscious participants tended to subscribe to the service under the low price level ($M_{low\text{-}price} = 5.62$, $M_{high\text{-}price} = 3.13$, $F(1,74) = 31.300$, $p < 0.001$), as shown by the solid line. Additionally, a two-way analysis of covariance (ANCOVA) in Table 11 validates the significant interaction between the level of price consciousness and the treatment ($p < 0.01$).

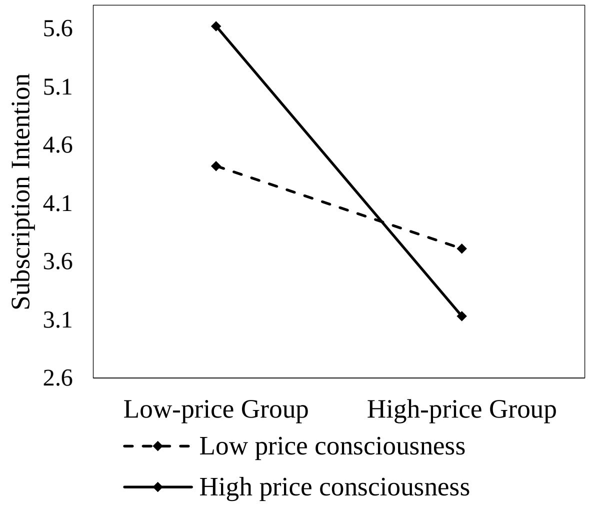


Figure 6. Mean Values of Subscription Intention Under Different Price Consciousness

Table 11. ANCOVA Results Between Price Consciousness and Treatment Group

	df	SSE	MSE	*F* value	*p*-value
Treatment	1	99.56	99.56	41.232	3.15e-09***
Price consciousness	1	3.11	3.11	1.289	0.259
Treatment × Price consciousness	1	22.59	22.59	9.355	0.003***
Tendency	1	100.81	100.81	41.753	2.59e-09***
Frequency	1	78.32	78.32	32.438	9.60e-08***
Budget	1	0.20	0.20	0.084	0.772
Gender	1	6.74	6.74	2.790	0.098*
Age	1	19.38	19.38	8.027	0.005**
Education	1	2.00	2.00	0.827	0.365
Familiarity	1	12.48	12.48	5.170	0.025**
Residuals	115	277.67	2.41		
Note: ****p* < 0.01; ***p* < 0.05; **p* < 0.1.					

We further investigated the role of the sunk cost fallacy. We initially presented model-free evidence that among subscribers, those in the low-price group exhibited higher susceptibility to the sunk cost fallacy compared to those in the high-price group ($M_{low\text{-}price} = 3.19$, $M_{high\text{-}price} = 2.43$, $F(1,70) = 8.773$, $p < 0.01$). This illustrates that lowering the fixed fee of the subscription service attracts a segment of customers who are more prone to the sunk cost fallacy. To validate this mechanism more rigorously, we categorized the participants into "high sunk cost bias" and "low sunk cost bias" groups, based on their responses to questions measuring sunk cost bias, and then conducted a two-way ANCOVA. Results presented in Table 12 and

Figure 7 reveal a significant interaction effect between susceptibility to the sunk cost fallacy and treatment group in terms of subscription intention. This affirms our argument that the downward price adjustment of the fixed fee attracts subscribers who are more susceptible to the sunk cost fallacy.

Movie consumption levels: We first conducted mediation analysis with *price* as the independent variable, *movie consumption levels* as dependent variables, and *subscription intention* as the mediator. As mentioned above, we measured participants' consumption levels through two indicators: consumption intention and the number of movies consumed.[16] The test of indirect effects revealed significant impact of price adjustment on both indicators of movie consumption levels through subscription intention (for consumption intention: $\beta = -0.8755$, $SE = 0.2178$, $CI_{95\%} = [-1.3350, -0.4804]$; for consumption numbers: $\beta = -1.9927$, $SE = 0.4941$, $CI_{95\%} = [-3.0525, -1.1078]$).

[16] Note that the consumption levels are not contingent on whether an individual has subscribed to the service. The purpose of this testing is to examine how consumption levels change when price adjustment of the fixed fee meets individuals with varying levels of susceptibility to the sunk cost fallacy.

Table 12. ANCOVA Results Between Sunk Cost Bias and the Treatment Group

	df	SSE	MSE	*F* value	*p*-value
Treatment	1	99.56	99.56	43.032	1.61e-09***
Sunk cost bias	1	18.44	18.44	7.972	0.006***
Treatment × Sunk cost bias	1	25.07	25.07	10.838	0.001***
Tendency	1	93.00	93.00	40.197	4.66e-09***
Frequency	1	76.64	76.64	33.126	7.29e-08***
Budget	1	0.30	0.30	0.128	0.721
Gender	1	5.38	5.38	2.326	0.130
Age	1	2.28	2.28	9.631	0.002***
Education	1	1.61	1.61	0.696	0.406
Familiarity	1	14.52	14.52	6.276	0.013**
Residuals	115	266.06	2.31		

Note: ****p* < 0.01; ***p* < 0.05; **p* < 0.1.

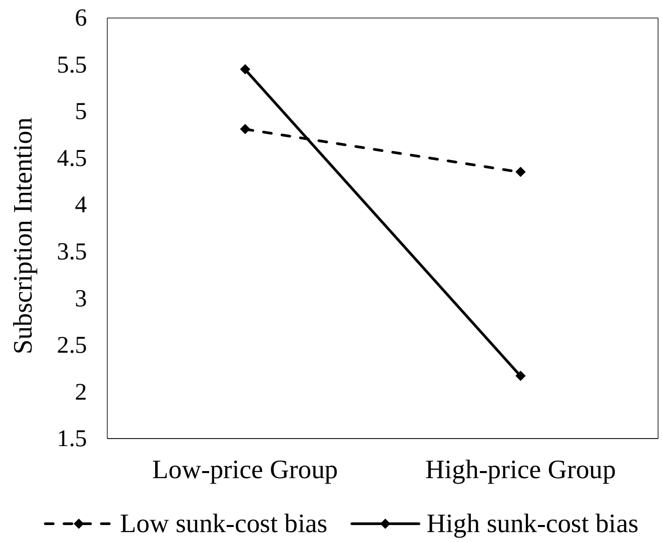


Figure 7. Mean Values of Subscription Intention Under Different Sunk Cost Bias

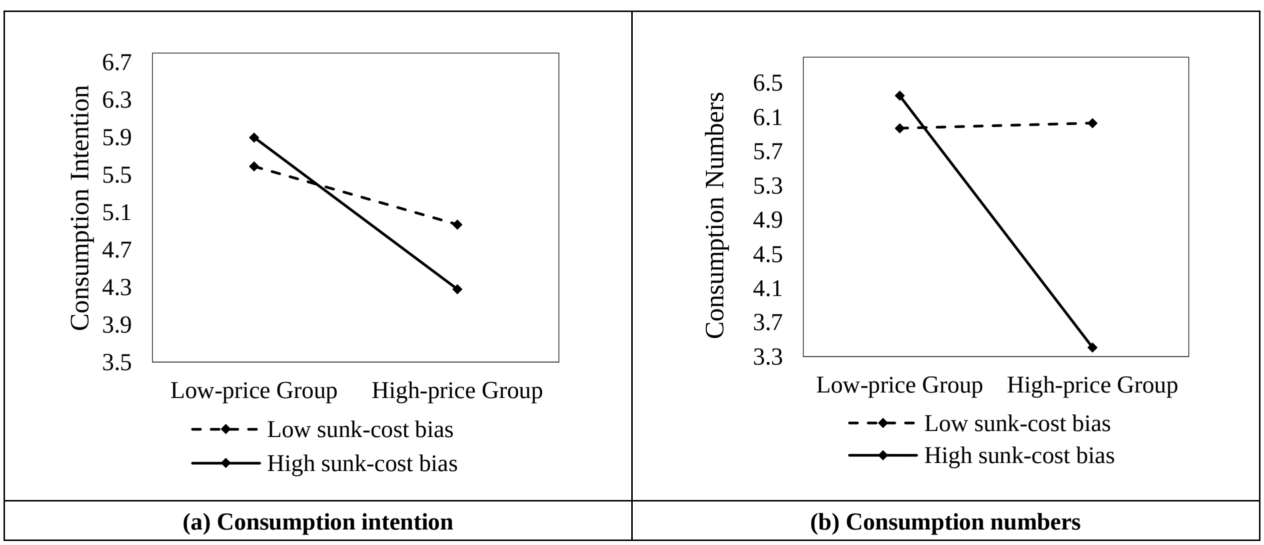


Figure 8. Interaction Effects Between Susceptibility to the Sunk Cost Fallacy and the Treatment Group

Then we examined the moderating roles of susceptibility to sunk costs on the relationship between the treatment group (i.e., price levels of the fixed fee) and the two variables related to consumption levels. Figure 8(a) shows there is a significant interaction effect between susceptibility to the sunk cost fallacy and the treatment group regarding consumption intention. More specifically, as shown by the solid line of Figure 8(a), participants with a high susceptibility to sunk costs demonstrated a higher consumption intention under the low-price condition (compared with the high-price condition) due to an increased willingness to subscribe to the service ($M_{low\text{-}price}$=5.90, $M_{high\text{-}price}$=4.28, $F(1,58)=20.46$, $p < 0.001$). However, as shown by the dotted line of Figure 8(a), the difference was not significant among those with a low susceptibility to sunk costs ($M_{low\text{-}price}$=5.59, $M_{high\text{-}price}$=4.97, $F(1,64)=2.218$, $p=0.141$). Similar results can be observed when the dependent variable is the number of movies consumed, as shown in Figure 8(b). Overall, these findings suggest that the downward fixed-fee adjustment is most effective in increasing consumption levels among participants with a high susceptibility to the sunk cost bias, as a result of their commitment to the subscription.

Movie consumption preferences: To validate H2 and its underlying mechanism, we similarly conducted two-way ANCOVA analyses to examine the interaction between susceptibility to sunk costs and the treatment group regarding participants' preferences for niche movies and their risk-taking intention. We found significant interaction effects for both dependent variables. Table 13 presents the corresponding ANCOVA results regarding the preferences for niche movies. Here, the interaction term is notably significant ($F(1,114)=37.810$, $p < 0.001$), lending support to hypothesis H2. This suggests that the effect of price adjustment on consumption levels is primarily attributed to participants' increased preferences for niche movies. Further,

Table 14 displays the results for risk-taking intention, where the interaction term is also significant ($F(1,115)=2.852$, $p < 0.1$). This validates our proposed mechanism: a downward subscription fee adjustment attracts individuals with high susceptibility to the sunk cost fallacy, subsequently leading to an increase in risk-taking intention. This explains the observed increase in consumption levels of niche goods.

To summarize, the well-controlled experiment not only allows us to replicate previous findings and test the proposed hypotheses at the individual level, but most importantly, it also enables us to test the mechanism in a more direct manner.

Table 13. ANCOVA Results for DV: Niche Movie Preferences

	df	SSE	MSE	*F* value	*p*-value
Treatment	1	6.67	6.67	16.641	8.40e-05***
Sunk cost bias	1	4.53	4.53	11.284	0.001***
Treatment × Sunk cost bias	1	15.17	15.17	37.810	1.18e-08***
Niche_before[a]	1	67.25	67.25	167.656	<2e-16***
Tendency	1	0.01	0.01	0.033	0.857
Frequency	1	2.71	2.71	6.744	0.011**
Budget	1	0.08	0.08	0.197	0.658
Gender	1	0.01	0.01	0.013	0.909
Age	1	0.06	0.06	0.160	0.690
Education	1	0.36	0.36	0.889	0.348
Familiarity	1	0.24	0.24	0.601	0.440
Residuals	114	45.73	0.40		

Note: [a] To account for the potential confounding effect of participants' inherent preferences, we measured their preferences for niche movies both before and after the subscription task and added the initial preference as an additional covariate. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 14. ANCOVA Results for DV: Risk-Taking Intention

	df	SSE	MSE	*F* value	*p*-value
Treatment	1	0.79	0.79	0.828	0.365
Sunk cost bias	1	0.12	0.12	0.129	0.720
Treatment × Sunk cost bias	1	2.73	2.73	2.852	0.094*
Tendency	1	17.30	17.30	18.051	4.39e-05***
Frequency	1	4.15	4.15	4.326	0.040**
Budget	1	0.64	0.64	0.668	0.415
Gender	1	2.87	2.87	2.998	0.086*
Age	1	6.75	6.75	7.047	0.009***
Education	1	2.31	2.31	2.414	0.123
Familiarity	1	5.94	5.94	6.195	0.014**
Residuals	115	110.21	0.958		

Note: Significance levels: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

9 Conclusion

Price adjustment is a common strategy employed by retailers to remain competitive, particularly when the adjustment is made towards a lower level. In this research, we examined how the price adjustment of a fixed-fee subscription service affected the consumption of information goods and explored the underlying mechanism. Since the up-front payment for a subscription service creates a sunk cost for its members, we hypothesized that a downward price adjustment would attract highly price-conscious consumers who are more susceptible to the sunk cost fallacy. This, in turn, would lead to a significant increase in the consumption of information goods. Results from a quasi-natural experiment on a movie subscription service verified our conjecture. We also observed that the marginal effect decreases over time, which can be explained by the "payment depreciation" of the sunk cost bias. People will gradually adapt to their upstream payment as time passes, which diminishes the sunk cost impact on further consumption. Heterogeneous analyses showed that niche information goods, especially those driven by narrow appeal and high quality, reap more benefits from such a downward price adjustment of a subscription service. To lend support to the underlying mechanism, we conducted a follow-up experiment, with two treatment conditions having different up-front fixed fees. In the experiment, we documented evidence that newly attracted subscribers experience high susceptibility to the sunk cost fallacy. Significant interaction effects between susceptibility to sunk costs and treatment conditions were observed in terms of consumption levels, risk-taking intentions, and preferences for niche information goods, affirming the underlying mechanism of sunk costs.

9.1 Theoretical Contributions

The present research makes several novel theoretical contributions that advance the understanding of price adjustment, sunk cost fallacy, and consumer behavior in subscription-based information goods. First, we extend the literature on price adjustment within fixed-fee subscription models, a topic that has received limited attention despite its growing relevance in the digital economy. While previous studies have primarily focused on shifts in consumption patterns when consumers transition from traditional to subscription-based channels, our study uniquely examines the causal impact of fixed-fee adjustments on overall consumption. We address the nuanced challenge that retailers face when the marginal cost of information goods is not zero, providing robust empirical evidence that lowering subscription fees leads to a measurable increase in consumption, particularly in the consumption of niche information goods. Our results not only confirm the economic significance of up-front fixed-fee adjustments but also offer a nuanced view of how these changes disproportionately benefit narrow-appeal, high-quality information goods.

Second, we enhance the understanding of the sunk cost fallacy by situating it within the context of subscription-based information goods, where the up-front payment acts as a sunk cost. Unlike conventional scenarios where sunk cost effects are tied to decisions between alternatives or project continuation, our context focuses on the consumption of information goods following a subscription payment. Prior research has documented that the psychological impact of past payments on future consumption tends to increase with the size of the payment. However, our findings challenge this notion by revealing that even small sunk costs, as seen in reduced subscription fees, can significantly influence consumption patterns. This highlights that the presence of any sunk cost, regardless of its size, can strongly influence consumer behavior in our context. Furthermore, our research shows that a reduction in subscription fees tends to attract highly price-conscious consumers, who are particularly susceptible to the sunk cost fallacy. This susceptibility leads them to invest more time and resources into consuming information goods, despite the lower initial cost. This distinction in context provides new insights into the mechanisms underlying the sunk cost fallacy in subscription models and offers a fresh perspective compared to more traditional settings.

Building on the above, our research contributes to the literature on the heterogeneity of sunk cost bias. While prior studies have focused on individual demographic characteristics within hypothetical scenarios, we expand this focus by examining how price consciousness, a characteristic closely linked to firms' price adjustment strategies, affects consumer susceptibility to the sunk cost fallacy. By identifying segments of consumers who are more likely to exhibit this bias, we not only clarify consumer behavior in response to price adjustments but also address controversial findings in earlier studies. Our work highlights the importance of considering marketing practices and aggregate outcomes, such as consumption patterns, in understanding sunk cost bias.

Finally, our study enriches the literature on price consciousness by challenging the traditional view that price-conscious consumers prioritize price over quality. We demonstrate that within the context of subscription-based information goods, these consumers do value quality, particularly when it comes to niche and high-quality offerings. This finding sheds light on the complex interplay between price sensitivity and quality considerations, offering a more nuanced understanding of consumer behavior. By illustrating how price-conscious consumers respond to price adjustments without sacrificing quality, our research contributes to a deeper comprehension of consumption decisions in digital markets.

9.2 Practical Implications

Our findings yield several practical managerial implications for subscription-based information goods providers. First, we provide insights into optimal pricing strategies that balance revenue optimization with value delivery across diverse consumer segments. A well-calibrated approach can incorporate tiered structures or dynamic models that adapt to varying price consciousness. This enables providers to cater to a broad user base while maximizing profitability. For instance, implementing a tiered pricing structure could involve offering basic, standard, and premium subscription levels, each with distinct features and price points. Dynamic pricing models could adjust prices based on factors such as usage patterns, time of day, or demand fluctuations, ensuring that prices remain competitive and reflective of the actual value delivered.

Second, with the observed declines in treatment effect over time, such depreciation of the sunk cost effect may have implications for how a subscription provider should schedule the payment of a subscription fee to avoid overconsumption. One potential approach is extending payment cycles (e.g., from monthly to semiannual) to moderate overall usage and encourage more thoughtful consumption. We also recommend implementing staggered payment schedules across the customer base to normalize aggregate consumption and help providers manage server loads more effectively. By offering flexible cancellation policies, such as prorated refunds or subscription pausing options, providers can reduce barriers to entry for new customers by alleviating their sunk cost biases, for example. These strategies collectively aim to optimize resource utilization and enhance operational efficiency by aligning consumption patterns with provider capabilities and costs. By modulating user behavior and smoothing demand fluctuations, these approaches can lead to more predictable resource allocation and improved service quality, ultimately benefiting both providers and consumers in the subscription-based information goods market.

Third, our findings reveal significant implications for market dynamics in the information goods sector. The research indicates that strategic downward price adjustments can substantially benefit niche information goods. This creates opportunities for smaller producers and specialized content creators to compete more effectively with established market leaders. Managers of information goods companies should consider implementing targeted price reductions, particularly in markets dominated by a few bestsellers. Such a strategy could lead to a more balanced product portfolio and potentially higher overall returns by capturing value from a wider range of market segments.

9.3 Limitations and Future Work

Our study, like many others, is not without limitations. However, these limitations open avenues for potential future exploration. First, our empirical analysis primarily relies on box office revenue data, which represents aggregate consumption without offering insights into individual behaviors and characteristics. This limitation stems from the nationwide scope of the MoviePass service, making it challenging to capture the diverse behaviors and characteristics of its vast user base. Thus, we can only leverage the downward adjustment of the up-front fee to analyze its impact on a general level applicable to all potential moviegoers in the US. Although this approach limited our ability to thoroughly test the proposed mechanism, the observed "payment depreciation" phenomenon and post hoc experiment mitigated this concern by allowing us to test the mechanism of sunk costs to some extent. In the future, a fine-grained dataset capturing individuals' behaviors would significantly enhance our understanding of the sunk cost fallacy, providing a richer analysis of its effects in practice. Second, although the up-front fixed fee is a commonly used pricing scheme for information goods subscription programs, other pricing strategies, such as the two-part tariff and three-part tariff, are also available. In these cases, consumers are required to pay additional charges, in addition to the time investment, to consume more information goods. Similarly, certain video subscription websites charge additional fees for newly released movies, even for premium consumers. For consumers, there is a trade-off between the up-front sunk cost and future cost when making decisions about further consumption. Thus, it would be intriguing to investigate whether the sunk cost can still increase further consumption in such cases. Third, we explore the treatment effect of price adjustment of the subscription service on the overall consumption level without considering the profits gained from subscription fees. As we have previously discussed, the marginal cost for subscription providers may not be zero, and any variation in consumption may impact both revenues and costs. Simply having higher consumption does not necessarily translate to better profits for the subscription provider. Thus, with a more extensive dataset, it would be interesting to conduct a thorough cost-benefit analysis, thereby assisting firms in optimizing their price adjustment strategies.

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Appendix A: Summary Statistics

Table A1. Summary Statistics for Key Variables

Variable	Description	Obs.	Mean	*SD*	Min	Max
Movie level characteristics of movie *i*						
RT_count_i	Number of comments for movie *i* in Rotten Tomatoes	200	23,060	29,027	53	207,992
$RT\_avg\_rating_i$	Average rating for movie *i* in Rotten Tomatoes	200	3.46	0.64	1.43	4.88
$IMDB\_count_i$	Number of comments for movie *i* in IMDB	200	116,483	148,777	250	658,116
$IMDB\_avg\_rating_i$	Average rating for movie *i* in IMDB	200	6.68	0.85	3.3	8.4
Movie-country level characteristics of movie *i* in country *j*						
$Release_{ij}$	Releasing days for movie *i* in country *j*	400	78.84	47.59	24	353
$Total\_revenue_{ij}$	Total revenue for movie *i* in country *j*	400	8,594,380	23,187,050	2188	220,009,584
Movie-week level characteristics of movie *i* in country *j* at week *t*						
$Revenue_{ijt}$	Weekend revenue for movie *i* in country *j* at week *t*	3995	1,908,730	8,779,494	11	220,009,584
$Release_{ijt}$	Number of days that movie *i* has been released in country *j* at week *t*	3995	49.82	41	3	353
$Theaters_{ijt}$	Number of screens showing movie *i* in country *j* at week *t*	3995	485.81	955	1	4,535
$Comp\_movie\_count_{ijt}$	Number of movies in play during the same week *t* of movie *i* in country *j*	3995	38.26	7.75	22	54
$Comp\_avg\_rating_{ijt}$ (from Rotten Tomatoes)	Average rating valence (from Rotten Tomatoes) for movies released during the same week *t* of movie *i* in country *j*	3995	3.52	0.13	3.17	3.77
$Comp\_avg\_volume_{ijt}$ (from Rotten Tomatoes)	Average rating volume (from Rotten Tomatoes) for movies released during the same week *t* of movie *i* in country *j*	3995	26,874	4,496	11,224	36,527
$Comp\_avg\_rating_{ijt}$ (from IMDB)	Average rating valence (from IMDB) for movies released during the same week *t* of movie *i* in country *j*	3995	6.77	0.20	6.33	7.19
$Comp\_avg\_volume_{ijt}$ (from IMDB)	Average rating volume (from IMDB) for movies released during the same week *t* of movie *i* in country *j*	3995	132,938	24,165	64,141	193,552
$Google\_trends_{ijt}$	Sum of Google trends index for movie *i* 1 week before week *t* in country *j*	3995	147.93	126	0	648
Pre_volume_{it}	Number of ratings for movie *i* 1 week before week *t* (from Rotten Tomatoes)	3995	88.69	680	0	27,455
$Pre\_valence_{it}$	Average rating for movie *i* 1 week before week *t* (from Rotten Tomatoes)	3995	3.09	1.34	0	5

Appendix B: Additional Details of the Post Hoc Experiment

The overall experimental procedures are visualized in Figure B1. Figure B2 shows the screenshot of the scenario description for the low-price treatment condition.

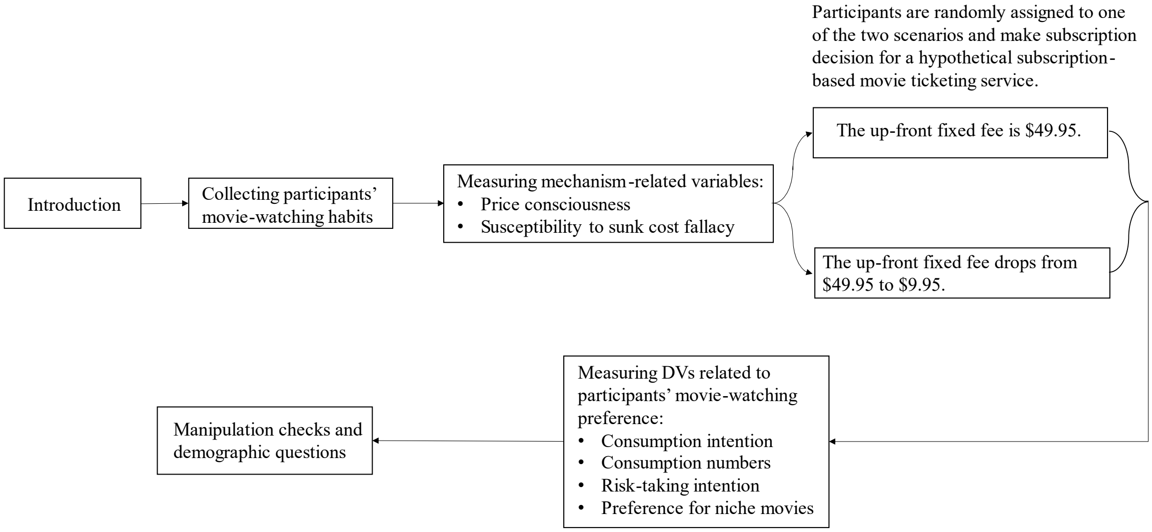
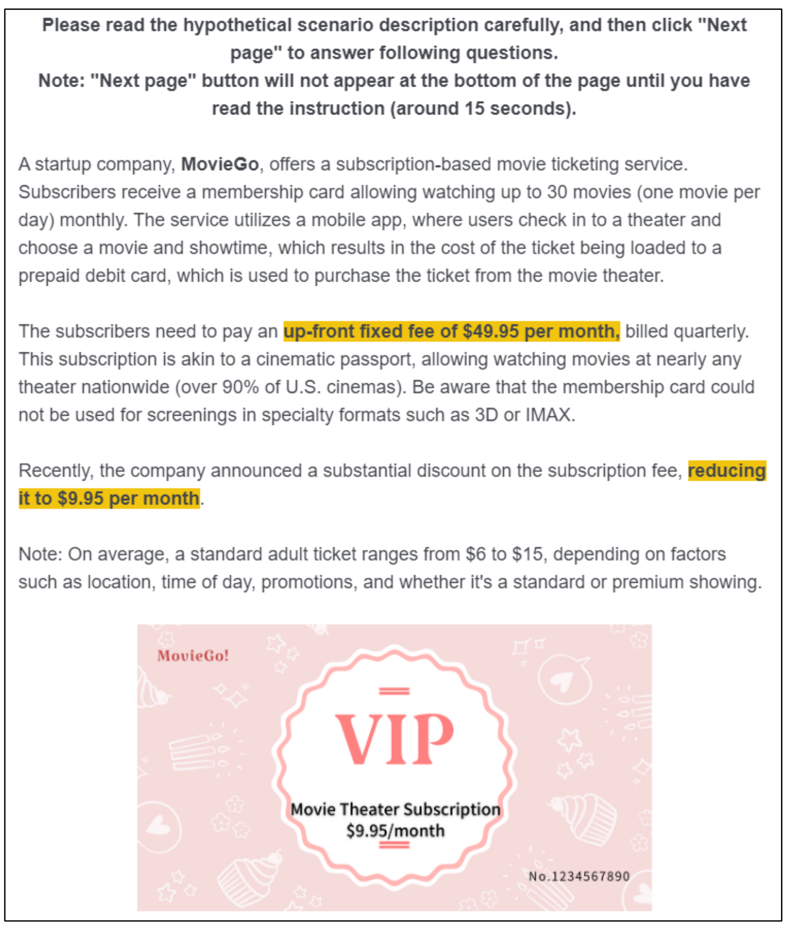


Figure B1. Procedure of the Experiment



Please read the hypothetical scenario description carefully, and then click "Next page" to answer following questions.
Note: "Next page" button will not appear at the bottom of the page until you have read the instruction (around 15 seconds).

A startup company, **MovieGo**, offers a subscription-based movie ticketing service. Subscribers receive a membership card allowing watching up to 30 movies (one movie per day) monthly. The service utilizes a mobile app, where users check in to a theater and choose a movie and showtime, which results in the cost of the ticket being loaded to a prepaid debit card, which is used to purchase the ticket from the movie theater.

The subscribers need to pay an **up-front fixed fee of $49.95 per month,** billed quarterly. This subscription is akin to a cinematic passport, allowing watching movies at nearly any theater nationwide (over 90% of U.S. cinemas). Be aware that the membership card could not be used for screenings in specialty formats such as 3D or IMAX.

Recently, the company announced a substantial discount on the subscription fee, **reducing it to $9.95 per month**.

Note: On average, a standard adult ticket ranges from $6 to $15, depending on factors such as location, time of day, promotions, and whether it's a standard or premium showing.

Figure B2. Screenshot of Scenario Description

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